Engineering User-Centric Smart Charging Systems

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Julian Huber, Karlsruhe 2020

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AEF	Average Emission Factor
APE	Absolute Percentage Error
ARIMA	Autoregressive-Integrated-Moving-Average (Model)
ANN	Artificial Neural Network
BEV	Battery Electric Vehicle
DSO	Distribution System Operator
EC	European Commission
EEG	Erneuerbare-Energien-Gesetz
EnWG	Energiewirtschaftsgesetz
EU	European Union
FEV	Full Electric Vehicle
GPS	Global Positioning System
ICE	Internal Combustion Engine
IS	Information System
KDE	Kernel Density Estimator
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MdAPE	Median of the Absolute Percentage Errors
MEF	Marginal Emission Factor
MLP	Multi-Layer Perceptron
PHEV	Plug-in Hybrids Electric Vehicle
PV	Photovoltaics
RQ	Research Question
SD	Standard Deviation
QR	Quantile Regression
ReLu	Rectified Linear Unit
RES	Renewable Energy Sources
RMSE	Root Mean Squared Error
SoC	State of Charge
TSO	Transmission System Operator
UCSCS	User-Centric Smart Charging Systems
V2G	Vehicle-to-grid

LIST OF SYMBOLS

β	Gradients in the regression models
$\dot{C}$	Maximum charging power
d	Parking duration
δ^{min}	Shortest possible charging duration
ϵ	Error term in regression models
F_τ	Forecaster using feature set τ
G_t	Hourly electricity generation
γ^p	Specific CO_2 emission factor
Γ_t^p	System-wide CO_2 emissions
h	Charging duration
$I_{t,n,\Lambda}$	Set of first n interrupted charging processes
ι	Duration of interruption
l	Trip Distance
L_a	Pinball Loss at a-% Quantile
L	Mean Pinball Score for all Quantiles
Λ	Interruption heuristic
n_t	Number of running charging processes at t
η	Electric efficiency
$P(Y)$	Probability distribution of random variable Y
Ψ	Charging strategy
q_a	a-% Quantile
Q	Set of Quantiles
s_t^k	Share of the technology k in the total generation in hour t
SoC^a	SoC at arrival
SoC^b	Buffer SoC
SoC^d	SoC at departure
SoC^f	Maximum SoC
$\bar{t}$	Length of a time step
t^a	Time of arrival
t^b	Time to reach SoC^b at $\dot{C}$
t^d	Time of departure
τ	Set of input features of a forecaster
V	Test statistic for Wilcoxen test
W	Energy demand of the charging process

y	Observation of a forecasted variable
$\hat{y}$	Prediction of a forecasted Variable
$z(t, n, \iota, \Lambda)$	Number of impaired mobility events
$Z(\Lambda)$	Share of impaired mobility events
ζ	Flexibility of the charging process

LIST OF INDICES

i	Index of parking event or charging process
k	Fuel type or generation technology
p	Power plant
s	Charging scenario
t	Discrete point in time
u	Experiment participant

Part I.

Introduction

CHAPTER 1

MOTIVATION

Road transportation accounts for 23 % of global carbon dioxide (CO_2) emissions (Santos, 2017). Besides CO_2, vehicles with internal combustion engine (ICE) also emit nitrogen- and sulfur-oxides and contribute to air pollution in cities. Battery-electric vehicles (BEVs), in contrast, do not emit any air pollutants locally and can operate CO_2 neutral if they are charged with electricity from renewable energy sources (RES). Governments and industry have set ambitious goals for increasing diffusion of BEVs to reduce carbon emissions from road transportation. For instance, the share of newly registered BEVs in the European Union (EU) has risen from practically zero to above two per cent during the last decade and is expected to multiply further (European Environment Agency, 2020).

The deployment of BEVs has large impacts on the energy system and the end-users of mobility systems. On the demand-side, BEVs couple the mobility sector to the electricity sector as BEVs source their energy from the electricity grid. An increase in BEVs adds a substantial group of new consumers to the electricity grid, which requires an increase in generation, transmission, and distribution capacity if charging is not coordinated (Hedegaard et al., 2012).

At the same time, energy systems' supply-side shifts towards high shares of RES to reduce CO_2 emissions. This shift presents an additional challenge, as electric power systems rely on flexibility to bridge outages in the generation, solve congestion of power lines and transformers, or adjust for forecasting errors to keep generation and consumption in balance. Flexibility is the capability of generators and consumers *'to follow different paths of action at a given point in time to provide a service for another entity'* (Lehmann et al., 2019). Traditionally, the primary sources of flexibility are large conventional power plants that can adjust their generation on short notice. RES generation, in contrast, often depends on weather conditions so that they cannot adjust their generation patterns in the same way. As more of the conventional power plants are being replaced by RES, the supply of flexibility decreases. RES generation depends on wind and sun and is often connected to lower grid levels. As grid infrastructure has typical lifetimes beyond 40 years (Moghe et al., 2011), the current grid was not designed considering these decentralized RES. In result, RES generation can cause congestion in the grid and further increase the demand for flexibility (Staudt, 2019). Likewise, planners of the existing distribution grid could not foresee new consumers like BEVs. Their additional demand can cause of congestion and increased demand for flexibility (Salah et al., 2015).

One solution to these challenges are reinforcements in grid infrastructure. Such reinforcements, however, are costly, take a long time, and meet increasing resistance in the population. Another approach to overcome these challenges is the development of smart grids. Smart grids use information technology to increase efficiency and flexibility in the energy system (Goebel et al., 2014). Following this notion, smart charging is the idea to use BEVs' charging sessions as a source of flexibility on the demand-side.

However, smart charging interacts with the everyday mobility behaviour of BEV users as BEVs differ from traditional cars with ICE in driving range and charging behaviour. While cars with ICE require users to stop at gas stations to refuel, BEVs can charge at any location that provides an electric outlet or a wall box. As the average parking duration at some of these locations can be several hours long (e. g., at home or work), charging must not always happen immediately but offers some flexibility in terms of energy demand and charging time. If the parking duration of a BEV exceeds the time needed for charging, a smart charging system can interrupt, shift, or reduce the speed of the charging session without affecting service quality. BEV users can provide time flexibility by allowing the smart charging system to fulfil the charging demand later than the system would by immediate charging at full charging power. Likewise, the BEV users can grant energy flexibility if they reduce their energy requirement accepting a state of charge (SoC) below 100 % at the end of the charging session. By providing this flexibility, the mobility sector could provide additional flexibility to the electricity and facilitate the integration of more RES.

To this end, researchers from energy informatics, engineering, and operations research develop methods to schedule the flexibility in BEV charging with different optimization objectives (García-Villalobos et al., 2014; Adika and Wang, 2014). However, this technical perspective often ignores the main bottleneck to charging flexibility, which is the willingness of the BEV users to accept flexibility during charging (Schmalfuss et al., 2015).

In particular, the potential of smart charging lies in the difference between what is technically feasible (i. e., energy requirement, parking duration, and maximum charging power) and to what degree the end-users accept to deviate from this technical potential (i. e., uninterrupted charging at the highest possible charging power). Smart charging systems will fall short in providing flexibility to the energy system if the BEV users do not accept to use smart charging instead of immediate charging in which case even the most advanced algorithms will have little potential left to optimize charging.

Smart charging systems have to address the BEV users' needs and objectives to unlock their flexibility potential to integrate BEVs as a chance and not a burden for the electricity system. While financial incentives might look like a promising incentive to encourage BEV users to use smart charging. At current market conditions, companies offering smart charging have little potential for cost savings and making revenues from smart charging (Brandt et al., 2017). As a result, the financial incentives they can set for the BEV users are rather small. Besides, Will and Schuller (2016) find no significant effect of financial incentives on the acceptance of smart charging in BEV users. Taking this in consideration, other ideas are needed to encourage BEV users to apply smart charging. More user-centric smart charging systems (UCSCS) should consider non-financial aspects and the users' preferences to design charging algorithms that act in the BEV users' interest and change their behaviour towards more flexible charging. However, designing new algorithms alone might not succeed, even if they consider the BEV users' objectives. While BEV users often intend to act sustainably and/or to save money by using smart charging (Will and Schuller, 2016; Schmalfuß et al., 2017), they might not always act in this expected way, as habit and social norms are also crucial drivers of human behaviour (Thaler and Sunstein, 2009). Such behavioural aspects are one reason that well intentions towards sustainability do not always translate into actions (Momsen and Stoerk, 2014). To overcome this gap between intention and action, UCSCS could not only offer better algorithms but help BEV users to overcome biases and act more rational through digital nudging. Besides, BEV users often only have a limited understanding of the energy system and their mobility behaviour (Biresselioglu et al., 2018). UCSCS could, therefore, use energy analytics to implement forecasts of CO_2 emissions to help by providing feedback on the effects of different charging decisions and forecasts of the users' mobility behaviour to provide decision support for the users in finding the right 'amount' of flexibility in their charging settings.

As prior research pays little attention to the BEV users' perspective in the design of smart charging systems, this dissertation strives to develop UCSCS: Such UCSCS consider the BEV users' objectives and integrate information in a way to encourage BEV users to contribute more flexibility to the electricity system.

CHAPTER 2

RESEARCH QUESTIONS

Smart charging systems are information systems designed to charge BEVs while offering demand-side flexibility for different objectives. Like other information systems, they collect, process, store, and distribute information from physical flow networks, e. g., the transmission and distribution system, and digital sensor networks (Piccoli and Pigni, 2008). Watson et al. (2010) argue that the information systems community should build information systems to utilize such information on supply and demand to make energy consumption more sustainable. Figure 2.1 adapts the energy informatics framework by Watson et al. (2010) for smart charging systems. From a technical perspective, smart charging systems provide a charging station to transmit electric power from the transmission and distribution system to the BEV. Besides, they can offer a graphical user interface and integrate information flows. Smart charging systems obtain connection and consumption data from the charging station, e. g., state of charge (SoC) and travelling data from the BEV, price and other information from energy markets, and BEV users' preferences entered in the user interface.

To guide further research, Watson et al. (2010) provide a set of research objectives regarding information system components and possible stakeholders (i. e., suppliers, consumers, and governments). For the case of engineering UCSCS, this dissertation focuses on the perspectives of consumers (i. e., BEV users) and suppliers (i. e., charging station operators), and the design of the user interface. The original research objectives in Watson et al. (2010) focus on energy efficiency. While energy efficiency is crucial in fossil energy systems, systems with high RES often have low marginal costs and emissions (Rifkin, 2014). Instead, the flexibility in energy demand becomes

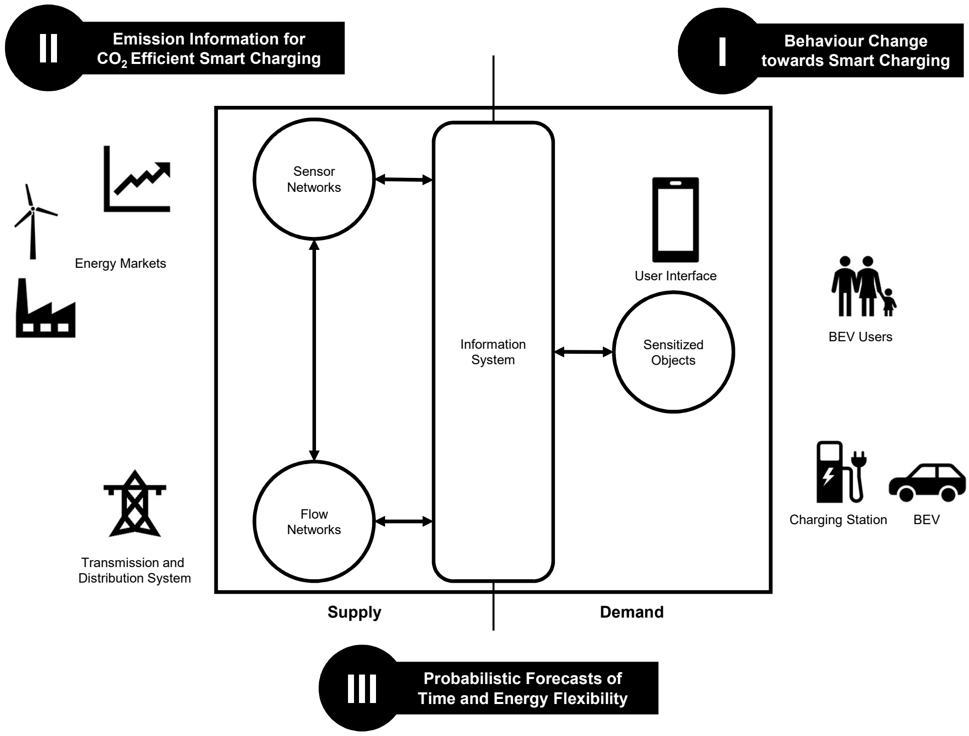

Figure 2.1.: Research objectives of this dissertation integrated into the energy informatics framework of Watson et al. (2010).

more critical to accommodate the fluctuations in RES generation. Smart charging is a promising source of demand-side flexibility if BEV users accept to charge their BEVs more flexibly. Adapting the research objectives for smart charging in energy systems with high shares of RES results in the following objectives which are addressed in this dissertation: First, information systems should change social norms to foster more sustainable behaviour by changing user behaviour towards smart charging. This dissertation utilizes ideas from behavioural-economics to increase the charging flexibility of BEV users. Second, information systems should provide users with information allowing them to act in a sustainable manner which is implemented by providing BEV users with information about expected CO_2 emissions during the charging process. The third objective of information systems is to use data to integrate supply and demand more efficiently. This objective is addressed by generating forecasts of the charging flexibility to improve coordination. These three research objectives provide the structure for the research questions in the following sections.

2.1. Behaviour Change towards Smart Charging

In an ideal world, each BEV is a device that offers an additional battery that could provide flexibility services to the energy system. As the first priority of BEV users is to cover their mobility needs, not the full technical potential can be used for such services as the users' mobility and charging behaviour determines how much socio-economical flexibility potential is available for smart charging.

A simple way to ascertain the individual potential of socio-economical flexibility and to use it as an input for smart charging systems is to ask the BEV users to state their charging preferences via a user interface (i. e., until which deadline they want to charge and how much energy they require). At this point, the energy informatics framework aims the first objective at designing user interfaces, which can change user behaviour towards more sustainable social norms (Watson et al., 2010). In general, BEV users would act more sustainable if they use smart charging instead of dumb charging, i. e., immediate charging (Kiviluoma and Meibom, 2011). While Will and Schuller (2016) show that acceptance of smart charging relies on different factors like the objective of the smart charging system, it is still unclear what drives the BEV users' decisions to use smart charging in different situations (Schmalfuß et al., 2017).

To enhance the BEV users' disposition to use smart charging and to apply the users' flexibility in a sustainable manner, objectives of smart charging systems should fit their needs. Most smart charging systems, however, will be supposedly built by charging station operators, aggregators, and system operators. To consider their requirements, this dissertation first analyses the objectives of smart charging systems and compares them to the objectives of the demand-side, i. e., BEV users.

The first research question (RQ) aims to identify common objectives that are likely to both convince BEV users to use smart charging systems and are practical for the charging station operators. This notion leads to the first RQ.

RQ 1 *Which objectives of smart charging are likely to motivate BEV users and show high technical potential?*

As there are still few regular BEV users and they might not have extensive knowledge about energy systems the first RQ is answered using a literature review and an expert survey. Cost reduction and RES integration are shared objectives between

BEV users and charging station operators and the technical potential for reaching these objectives relies on the flexibility in BEV users' charging settings. How much flexibility the BEV users offer might, in turn, depend on the objective of the smart charging system. UCSCS presenting users the right objective might increase their willingness to use smart charging. Research in behavioural economics and information systems research shows that information systems can be designed in a way that they actively nudge people towards more sustainable behaviour (Weinmann et al., 2016). Digital nudging helps to influence people into making more sustainable decisions, as, e. g., to adopt green electricity contracts (Schultz et al., 2007). This dissertation looks into ways to transfer the concept of digital nudging to the user interface of smart charging systems (compare Objective I in Figure 2.1). In particular, the second RQ is used to evaluate how information systems can use framing messages towards different objectives to nudge BEV users' behaviour towards more flexibility in their charging settings.

RQ 2 *To what extent can framing messages in user interfaces influence the flexibility in BEV users' charging settings?*

While not all BEV users are willing to charge flexibly as a default, some BEV users are highly motivated to charge more flexibly if this allows charging at times when RES are available in the energy system (Huber et al., 2019a; Will and Schuller, 2016). However, BEV users usually cannot know whether the RES feed-in is low or high during their charging session. Without this information they cannot follow their intentions to act in a sustainable way. The next objective of this dissertation is to integrate data to enable BEV users to charge or provide flexibility to minimize CO_2 emissions during charging.

2.2. Emission Information for CO_2 Efficient Smart Charging

Given a non 100 % RES energy system, charging BEVs is not always sustainable. For instance, charging a high number of BEVs with electricity from conventional energy resources can even increase a country's CO_2 emissions compared to using cars with

ICEs (Jochem et al., 2015). However, smart charging has the potential to minimize carbon emissions if the BEV users are flexible (Hoehne and Chester, 2016), even in the current energy system without 100 % RES.

UCSCS could help users to manage charging and increase their sustainability fulfilling the second objective of information systems to increase flexibility (Watson et al., 2010). To this end, UCSCS should provide the BEV users with feedback on when to charge their BEVs in the most sustainable fashion to minimize CO_2 emissions compared to uncontrolled charging. Such minimization requires a forecast of the CO_2 emissions of the relevant energy system during the charging session. Based on such an forecast the smart charging system could schedule the charging session to charge at times with low CO_2 emissions. To reach this goal, the smart charging system has to integrate data from energy markets to provide feedback and decision support in the user interface (see Objective II in Figure 2.1). In a first step, this dissertation evaluates the effects of smart charging on CO_2 emissions given the German energy system.

RQ 3 *At what times during the day can smart charging achieve the highest CO_2 emission savings?*

To answer RQ3, data from energy markets is applied to help BEV users making more sustainable charging decisions. As the CO_2 emission factors of the German energy system show substantial variation, BEVs cause lower CO_2 emissions if they are charged during hours with high PV generation around noon. Shifting charging loads has an impact towards the energy systems' CO_2 emission as new generators are dispatched to adjust for the shifted consumption (e. g., if a coal power plant ramps up to fulfil charging demand). Literature proposes to use marginal CO_2 emission factors to analyse such effects (Olkkonen and Syri, 2016). Marginal emission factors of an energy system can look different from average emission factors in both in overall level and timing. As estimating marginal emission factors requires more data and computation than estimating average emission factors, the fourth RQ evaluates whether designers of UCSCS can use average CO_2 emission factors to approximate marginal emission factors.

RQ 4 *What are the absolute and temporal differences in CO_2 emission saving potentials assessed with average and marginal emission factors?*

Analyzing the average and marginal emissions of the German energy system based on generation data of power plants larger than 100 MW shows that average emission factors underestimate CO_2 saving potentials of smart charging and can recommend shifting loads towards hours with high marginal emissions. Therefore, average emission factors should not be used to approximate marginal emission factors. Researchers evaluated the potential CO_2 minimization using smart charging based on marginal emission factors under perfect foresight (Hoehne and Chester, 2016; Jochem et al., 2015). However, it is still unclear whether this potential could be realized by a smart charging system that does not have perfect foresight of marginal emission factors. Implementing smart charging systems requires short-term forecasts for marginal emission factors. The next research question evaluates the performance of a forecast-based smart charging system, that predicts the marginal CO_2 emission factors and optimizes the emissions during charging.

RQ 5 *To what degree can a forecast-based system realize the CO_2 emission saving potentials of a perfect foresight scenario?*

Short-term forecasts of marginal emission factors are sufficiently accurate to obtain substantial savings in CO_2 emissions. Using these forecasts, the integration of external information can make smart charging more sustainable. The forecast-based UCSCS can provide BEV users with feedback on how much CO_2 they could avoid if increasing the flexibility in their charging session. However, the users still have to decide how flexible they want to charge and enter the flexibility into their smart charging system. Here, forecasts of charging flexibility could provide user assistance in recommending the preferable amount of flexibility in a charging situation or even automatize the process of entering the charging settings making the process even more convenient. The next section expands on forecasts that can help to predict the flexibility in BEV charging, which is the basis for effective integration of supply and demand of charging energy.

2.3. Probabilistic Forecasts of Time and Energy Flexibility

BEV users might know best when and how they want their BEV to charge. Unfortunately, manually entering the preferred charging settings at every time the BEV is connected to the charger requires effort and is inconvenient. Convenience, however, is a crucial factor in the acceptance of smart charging systems (Schmalfuss et al., 2015). Also, Lee et al. (2019) show that BEV users often perform poorly when asked to provide estimates of desired SoC and planned time of departure. For such reasons, Flath et al. (2012) propose decision support systems for BEV charging to obtain a higher degree of automatization, which could help to make smart charging more appealing and could lead to more flexibility on the demand-side to fulfill the third research objective (see Objective III in Figure 2.1).

Schuller et al. (2015) find that the flexibility in BEV charging differs for different user types, while Sadeghianpourhamami et al. (2018) identify specific behavioural clusters in parking situations that show varying time and energy flexibility. Information systems can integrate data from the supply and demand-side to increase the efficiency of the energy system (Watson et al., 2010). Following this idea, this dissertation evaluates the potential of information from travel data and charging history of BEVs to predict time and energy flexibility in BEV charging.

As mentioned above, time flexibility relies on the parking duration at the charging station. In contrast, energy flexibility depends on the energy requirement of the charging session which correlates with the distance of the following trips. Many parking events of a commuter car are shorter than one day. Still, there are single events when the parking duration is much longer than a single day, e. g., during the weekend or when the commuter is on vacation. Distributions of both parking duration and energy requirements of BEVs are very skewed. As a result of this skewness, point forecasts of average parking duration and trip distance can be far off. To mitigate this problem, the next research objective evaluates how probabilistic forecasts that contain information about the expected distribution can improve smart charging.

While prior research (Schuller et al., 2015; Sadeghianpourhamami et al., 2018) indicates that information on the user and parking situation, e. g., location and timing, gives insights on the expected flexibility, there is little research on the benefits of including travel data of BEVs. This data is of particular interest, as for the moment only some charging station operators (e. g., car manufacturers) have access to this kind of data and could obtain an advantage in using it for smart charging.

To evaluate whether these charging station operators and BEV users can use this data to forecast the flexibility in smart charging, this dissertation focuses on the following research question.

RQ 6 *To what extent does travel data improve the accuracy of probabilistic forecasts for parking duration and next trip distance of individual parking events?*

For both, parking duration and trip distance, using travel data as an additional input can improve forecasting accuracy. However, the improvements in forecasting accuracy obtained by integrating the additional data are rather small, so the question arises, whether this improvement has any practical implication. To evaluate whether the probabilistic forecasts can improve scheduling of BEVs' charging sessions in practice, the next step is to apply the forecast in a case study. This case study is to use the probabilistic forecasts in a smart charging coordination scheme that interrupts charging (e. g., in case of congestion). The scheme aims at minimizing the interruption of BEVs with low flexibility which could result in an insufficient charge for the BEV users' next mobility event and impair their mobility.

RQ 7 *What number of mobility impairments can be avoided using a smart charging strategy based on probabilistic forecasts as compared to point forecasts?*

Using probabilistic forecasts based on travel data improve the scheduling of BEVs compared to point forecasts allowing them to interrupt more charging processes without affecting the BEV users. In this way, forecasts can increase the flexibility for charging station operators on the supply-side and also enhance comfort for BEV users on the demand-side.

By answering the research questions above, this dissertation contributes to the integration of BEVs into the energy system by increasing the socio-economical flexibility of BEV users based on the design of UCSCS. The results show that UCSCS can apply digital nudging to increase the amount of flexibility offered by BEV users. Besides, UCSCS can use data to provide BEV users with feedback on CO_2 emissions during charging and realize CO_2 minimization potentials. Finally, probabilistic forecasting of charging flexibility can help to use a higher share of flexibility in BEV charging without negatively affecting BEV users' mobility needs. These findings can help to increase BEV users' acceptance of smart charging and allow to include a higher number of BEVs and RES into the electricity system without increasing grid and generation capacity.

CHAPTER 3

THESIS STRUCTURE

This dissertation comprises 13 chapters which are grouped into five parts. Figure 3.1 outlines this structure. After the first part establishes the motivation and research agenda, the second part lays the foundations for answering the research questions. While Chapters 4 and 5 describe the role of flexibility in power systems and the potential of smart charging to provide demand-side flexibility, the remainder of Part II provides theoretical foundations for the following analyses. Chapter 6 provides the essential terminology about short-term forecasting used in the following parts. Chapter 7 adds a concise overview of choice architecture and digital nudging. This idea of guiding users towards better decisions by conscious design of the decision environment is the basis of the evaluations in Part III and gave inspiration for the CO_2 feedback and the flexibility forecasts in Part IV. Putting these four chapters in a dedicated Part II allows readers to understand the context and concepts independent from their application to smart charging in Part III and IV. This structure allows readers to understand the key ideas behind this dissertation and transferring them towards new applications.

The third part focuses on how to change BEV users' behaviour towards the use of smart charging systems. Chapter 8 identifies the objectives that motivate BEV users to use smart charging and evaluates them in an expert survey. Based on these objectives, Chapter 9 describes a scenario-based choice experiment that evaluates the potential of digital nudging to apply these objectives to make users more flexible in their charging settings.

Part IV elaborates data-driven solutions to allow users to charge their BEVs using a higher share of RES and assists them with forecasting the preferable amount of

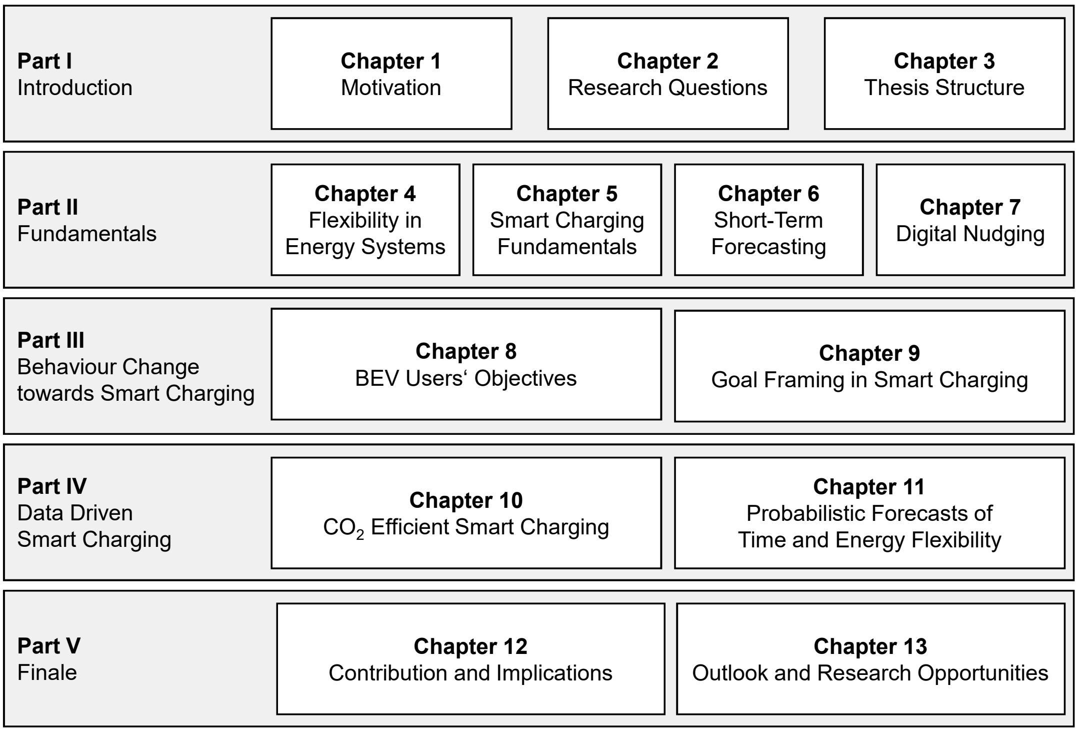

Figure 3.1.: Structure of this dissertation.

flexibility in their charging settings. Chapter 10 proposes a methodology to forecast the carbon emissions of individual charging sessions, derived from open-data from the German power system (i. e., plant commitment, plant efficiency, and weather data). Smart charging systems can apply such forecasts to use the flexibility in individual charging sessions to minimize carbon emissions charging during hours with low carbon emissions. Besides avoiding carbon emission, this methodology can provide BEV users with feedback on the benefits of their decision to use smart charging. Such feedback could provide additional motivation for BEV users that are motivated by the integration of RES.

However, to profit from the benefits of smart charging, BEV users still have to decide how much flexibility they are ready to provide during their charging session. For each individual charging session, charging station operators or BEV users have to determine the temporal deadline and energy requirement of the charging session. Chapter 11 describes how data from BEVs and charging stations can be used to provide a probabilistic forecast of the flexibility in BEV charging. The chapter describes the development of probabilistic forecasts of parking duration and energy requirement of individual charging events and evaluates the forecasts performance in a case study for the scheduling of a portfolio of BEVs.

The dissertation ends with Part V. Chapter 12 summarizes the findings and the contributions of this work, discusses its limitations, and outlines practical implications of the findings to foster the integration of BEVs and their users into the electric energy system. Finally, Chapter 13 offers an outlook on new research opportunities.

While this dissertation is individually composed, parts of this work rely on the contributions of my published or unpublished collaborative papers. As these papers are joint efforts of several collaborators, I disclaim these parts clearly and refer to the authors as a group (*'we'*).

List of Publications

Selected parts of this dissertation are based on the following published or working papers.

- Huber, J., Schaule, E., Jung, D., and Weinhardt, C. (2019c). Quo vadis smart charging? a literature review and expert survey on technical potentials and user acceptance of smart charging systems. World Electric Vehicle Journal, 10(4):85. [Chapter 5 & 8].

- Huber, J., Jung, D., Schaule, E., and Weinhardt, C. (2019a). Goal framing in smart charging - increasing bev users' charging flexibility with digital nudges. In Proceedings of the 27th European Conference on Information Systems (ECIS), Stockholm and Uppsala, Sweden, June 8-14, 2019. [Chapter 9]

- Huber, J., Lohmann, K., Schmidt, M., and Weinhardt, C. (2020b). Carbon efficient Smart Charging using Forecasts of Marginal Emission Factors. [Working Paper submitted to Journal of Cleaner Production]. [Chapter 10]

- Huber, J., Dann, D., and Weinhardt, C. (2020). Probabilistic forecasts of time and energy flexibility in battery electric vehicle charging. [Applied Energy, 262]. [Chapter 11]

Other related Publications

- Huber, J., Wolff, M., and Jung, D. (2018e). Is charging fright the new range anxiety? designing digital nudges to increase charging flexibility. In 31st Conference on Environmental Informatics (EnviroInfo 2018), Garching, 5.-7. September 2018. LRZ, Garching.

- Huber, J., Schaule, E., and Jung, D. (2018d). How to increase charging flexibility? – developing and testing framing nudges for bev drivers. In 31st Conference on Environmental Informatics (EnviroInfo 2018), Garching, 5.-7. September 2018. LRZ, Garching.

- Huber, J. and Weinhardt, C. (2018b). Waiting for the sun-can temporal flexibility in bev charging avoid carbon emissions? Energy Informatics, 1(1):49.

- Lehmann, N., Huber, J., and Kießling, A. (2019a). Flexibility in the context of a cellular system model. In 2019 16th International Conference on the European Energy Market (EEM), pages 1–6. IEEE.

- Huber, J., Richter, B., and Weinhardt, C. (2018c). Are consumption tariffs still up-to-date? an operationalized assessment of grid fees. In 2018 15th International Conference on the European Energy Market (EEM), pages 1–5. IEEE.

- Huber, J., Köppl, S., Klempp, N., Schutz, M., and Heilmann, E. (2018b). Engineering smart market platforms for market based congestion management. In Proceedings of the Ninth International Conference on Future Energy Systems, pages 544–549. ACM.

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Part II.

Fundamentals

CHAPTER 4

FLEXIBILITY IN ENERGY SYSTEMS

Reliable and economic access to electrical power is the premise for numerous everyday processes in industrialized societies and drives modern economies. From the beginnings of electrification during the last two centuries, electricity has been generated burning fossil fuels and harnessing hydropower. Electricity and heat generation has become by far the largest source of human CO_2 emissions (International Energy Agency, 2020). As human CO_2 emissions contribute to global warming and climate change (IPCC, 2020), governments aim to generate more electricity from RES using wind, geothermal, or solar energy. Establishing an environmental friendly supply of electric energy also allows to decarbonize parts of the heating and mobility sector (see Chapter 10). This chapter describes the current transition of the German electricity system.

Integrating new generators and consumers requires modifications to the energy system. During this transition, the energy system must balance the three conflicting goals of security of supply, sustainability, and economic efficiency. In today's energy systems, security of supply is mostly ensured by redundancies in the infrastructure and a high share of conventional generators, making the energy systems resistant against technical failures and independent from intermittent renewable generation. On the other side, today's energy systems based mainly on conventional generation are not considered sustainable as they still require mining for fossil fuels and emit pollutants and CO_2. Increasing the shares of RES would result in less pollution and lower cost. However, such a system would fall short in terms of security of supply as the supply in energy depends on wind and sun. Compensating the volatility of RES with high redundancy would result in high capital cost for generation and transmission equipment.

Another way to offset the volatility in the generation in energy systems with high shares of RES is to use flexibility. Flexibility is the ability to change the feed-in or feed-out pattern to provide a service to the energy system. To replace large conventional power plants, the energy systems have to introduce new sources of flexibility throughout the electric value chain to provide reliable, sustainable, and inexpensive electricity. The remainder of this chapter provides an overview of the electricity value chain in the traditional structure from power generation in Section 4.1 down to the electric devices and appliances of end-users in Section 4.3 discussing the changes and challenges introduced by the energy transition towards a higher share of RES in the German energy system.

4.1. Power Generation

Electricity in Germany (in 2019) is mainly generated by large (>100 MW) central power plants. Figure 4.1 shows that lignite, hard coal, and natural gas power plants generate 39.5 % of the total electricity (514.86 TWh). Such fossil power plants burn fossil fuels to fire a stream cycle that drives an electric generator. The electrical generators in these power plants generate alternating current at 50 Hz and feed it into the power grid on medium and high voltage levels. This frequency runs through the entire power grid from the generators to the consumers, which either work at 50 Hz alternating current or use a rectifier to convert the electric energy to direct current (e. g., for charging BEV batteries). Nuclear power plants work with the same principle as fossil power plants. However, thermal energy originates from a self-sustained nuclear chain reaction. Nuclear energy provides 13.9 % of generation but will be discontinued in Germany by the end of 2022. Both fossil and nuclear power plants can reliably provide electricity and flexibility, but emit pollutants and nuclear waste.

Emission-free RES provide an increasing share of the generation (46 %). Similar to fossil power plants, wind farms, and hydroelectric power plants feed electric power into the high and medium voltage grid. In contrast, individual wind turbines, smaller biomass, and photovoltaic (PV) plants feed into lower voltage levels. As wind turbines and PV both depend on the weather conditions, a stable energy supply with high shares of RES requires flexibility to provide system reserve (Hirth, 2015).

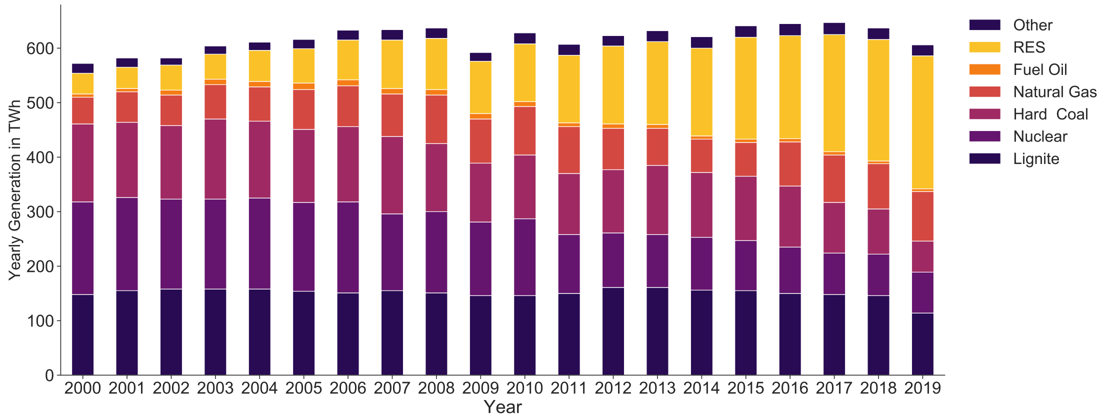

Figure 4.1.: Electricity Generation in Germany from 2000 to 2019 based on data by bdew (2019).

On an economic level, there are differences in the cost structure of generation from fossil and RES generation. In conventional power plants, the marginal costs of electricity are mainly determined by fuel costs. In contrast, wind and PV have marginal costs close to zero, as their generation depends only on wind and sun and does not require additional input.

This difference leads to a fundamental change in many energy markets. In energy systems with high shares of fossil generation, the generators line up in a merit order based on their marginal costs. When the demand for electricity is low, only the cheapest power plants (with the lowest marginal cost) are in operation as the market price surpasses their marginal costs. With increasing electricity demand and electricity prices, it becomes attractive for more expensive power plants to generate and sell electricity. In this way, the generation of electricity follows a rather inelastic demand. However, RES with marginal costs close to zero have little incentive to react to changes in the electricity demand as their marginal costs are usually below the market price. In addition, RES cause a *merit order effect* by shifting the merit order to the right and reducing the number of hours in which expensive fossil power plants can make a positive contribution to their profits. The reduction in profits can lead to a missing money problem which makes it unattractive for fossil generators to stay in the market as they struggle to cover their capital costs (Hogan, 2017). If this effect drives flexible conventional power plants out of the electricity market (see Figure 4.1), other sources and mechanism must provide the flexibility for stable operation (Haas et al., 2013).

4.2. Power Transmission and Distribution

The German distribution and transmission system is divided into four transmission and 880 distribution systems (European Commission, 2020). While the distribution systems distribute electricity to the individual end-users, the transmission system transports large amounts of power over several hundred kilometres.

As a large number of wind turbines is installed in the north of Germany, and primary consumers are located in the south, electric power in the German transmission grid flows mainly from north to south. Not considering power flow, the German electricity market assumes the transmission and distribution system to be a 'copper plate' so that all market results can be realised. The assumption is that electric energy can be transferred from between all grid connection points without losses and bottlenecks. In consequence, all actors on the wholesale electricity markets see the same electricity price without any locational differences. As a result, there are no incentives for generators to adapt generation to power-flow restrictions. In reality, electricity is transmitted and distributed not through a 'copper plate' but via cables and overhead lines. Regulated transmission system operators (TSO) manage the transmission network in Germany. The transmission network transmits high amounts of energy over long distances and is operated with high and very high voltage (i. e., 120 to 380 kW) to reduce losses. This flow regularly causes horizontal congestion in the transmission grid, which is resolved by re-dispatch (EnWG §13.1). Here, TSOs re-dispatch the power generators initially dispatched by the market result using the flexibility of conventional power plants. For this purpose, the dispatched generators on one side of the congestion have to reduce generation. These generators are mostly wind parks and lignite power plants in the north-eastern part of Germany (Staudt et al., 2018b). On the other side of the congestion, generators increase their generation to keep the energy balance. In this way, the flexibility of conventional power plants compensates for limited transmission capacity. These generators are often fossil power plants in the southern part of Germany which are compensated based on their generation costs.

The distribution system delivers electric power to the end-users through the medium and low voltage grid (i. e., below 120 kW). While the German transmission grid is 131,000 km in length, the medium and low voltage grid is ten times longer (BNetzA, 2020). Accordingly, the medium-voltage and distribution networks are currently still equipped with much less sensor technology than the transmission grid. As a result, grid failures and congestion in the distribution system are more challenging to discover and solve.

Like the horizontal congestion (i. e., the congestion of a transmission line) that occurs almost daily in the transmission network, there are three typical types of congestion that happen in the distribution system (Huber et al., 2018b).

First, one type of congestion occurs, if RES feed-in leads to a reversal of the load flows where the electric power flows from the prosumers to the higher load level and cause horizontal congestion (Agalgaonkar et al., 2013). Second, new types of consumers, e. g., heat pumps and BEVs, have high power requirements and can be a further cause of congestion on lower grid voltage. Third, vertical congestion occurs when the maximum current at transformers is exceeded. Such congestion often occurs in the distribution grid. Triggers are too much electricity from PV or too many BEVs charging simultaneously (Salah et al., 2015). Flexibility can mitigate these congestions by reducing the charging power of the BEVs or by using excess PV power locally and not feeding it into the grid.

If these solutions are not possible, feed-in management (EnWG §13.2) allows grid operators to interrupt RES connected to their grid. On the demand-side, grid operators can interrupt some electric consumers, e. g., heat pumps and BEVs (EnWG §14a). These electric consumers pay a reduced grid fee and can be interrupted by the DSO if necessary. Last, independent of generation and consumption, grid congestion can occur if equipment fails or is maintained according to schedule. Such congestion is rather uncritical, as it is either rare (e. g., failures) or predictable (e. g., scheduled equipment maintenance).

However, unforeseen outages and miscalculations can result in deviations between supply and demand. In electricity systems with alternating current, supply and demand must be in balance at any moment to retain a stable grid frequency at 50 Hz. Actors on the wholesale electricity markets are obliged to have a balancing group which contains all electricity procured and sold in each 15 minute interval. If market participants miscalculate and their balancing group is not even, they can use flexibility from generators or consumers or have to pay for imbalance energy. The TSOs, who are responsible for the system's stability and ensure a safe operation at a grid frequency of 50 Hz, operate ancillary markets that provide this flexibility to compensate for short-term imbalances in generation and demand.

Sufficient supply of flexibility is crucial to congestion management and system stability. As the shift towards RES reduces the supply of flexibility in the energy systems supply-side, the next section discusses to what degree the demand-side could supply this flexibility.

4.3. Retail and Consumption

Despite these challenges, end consumers suffer on average, only five to ten minutes of power outages per year (Bundesministeriums für Wirtschaft und Energie, 2020). This level of security is crucial as reliable electric power is the basis for modern living, production, and digital services.

Figure 4.2 shows that industry is the largest consumer at 47 % in 2019. In some industries, electricity consumption contributes a substantial share to cost. Such electricity-intensive consumers (e. g., pulp and paper and chemical industry) often have elaborated energy management systems and business divisions for energy procurement which trade energy on wholesale markets or over-the-counter. Companies that participate in wholesale electricity markets are obliged to create a balancing group for accounting reasons. Within a balancing group, the amount of electricity purchased on the wholesale markets or generated must be in balance with the electricity consumed or supplied to consumers at any given time. Keeping balance within each group ensures that supply and demand in the electricity system is in balance at any moment, and the frequency stays at 50 Hz.

Residential consumption and business, sales, and services both account for around a quarter of German electricity consumption. As most of them are smaller consumers, they do not participate in wholesale markets but sign long-term electricity supply contracts with energy supply companies. These contracts usually determine a base-price, a working-price, and in some cases a peak-price (Huber et al., 2018c). If these rates do not change over the lifetime of the contracts, the electricity procurement

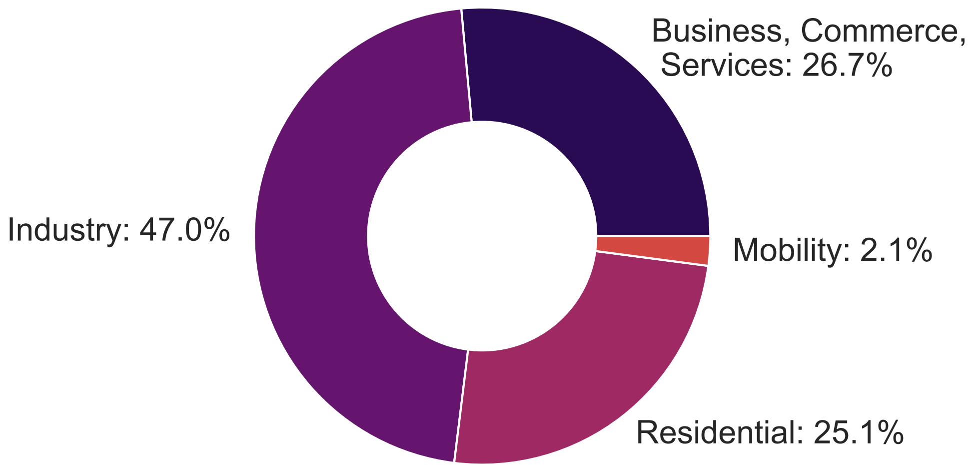

Figure 4.2.: Net electricity consumption in Germany in 2018 based on data by bdew (2019).

costs are only dependent on the energy consumption and load peaks during the billing period and do not provide an incentive for the consumers to provide flexibility (e. g., reducing consumption in peak hours). The energy supply companies aim to predict this inelastic demand of their customers and try to match it with their generation and purchases on wholesale markets.

In 2019 the mobility sector only accounted for 2.1 % of electricity consumption. However, the electricity consumption of the mobility sectors will substantially increase if the forecasts of BEV diffusion in Germany are correct (Gnann et al., 2015). As BEVs can charge large amounts of electricity in a short period, they can put more tension on the grid (i. e., cause congestion) and make predictions of consumption more difficult (i. e., result in lager forecasting errors).

As demand-side flexibility allows to change consumption patterns, it could alleviate both problems. Typical sources of demand-side flexibility are industrial processes that are suitable for demand response measures and can provide several kW of flexibility (Huber et al., 2018a). Such lager consumers are usually connected to the medium-voltage grid and are already integrated into the mechanism of the TSOs' ancillary markets. Smaller consumers in households, however, also have substantial flexibility but are too small to trade effectively on the central markets (Gottwalt et al., 2016). In contrast to larger consumers, they can provide flexibility in lower voltage levels, where congestion caused by PV systems and BEV are expected to increase the demand for flexibility.

Grid operators, energy supply companies, and aggregators integrate smaller flexibility potentials using various flexibility mechanisms. Lehmann et al. (2019) distinguish a set of eight valid mechanisms that are suitable for integrating small-scale flexibility into the energy system. How much of the technically available flexibility potential of an electric system is usable depends on socio-economic factors (i. e., how much flexibility the operator wants to offer at what price). Flexibility can be made available to third parties via various mechanisms. For demand-side flexibility, two mechanisms are particularly relevant.

Instead of fixed-rate energy contracts, energy supply companies can offer time-variable rates to consumers. As a result, consumers can then control their generators and electrical consumers using an energy management system to profit from times with low electricity prices. In this way, the energy supply company can influence consumption and generation of the consumers. One advantage of this decentralised mechanism is that that consumers do not have to communicate the flexibility potential in advance.

However, this mechanism is not suitable for applications where flexibility must be known in advance and reliability of the available flexibility is an issue. Other mechanisms solve this problem by describing the flexibility potential explicitly in advance using a suitable data model (Mauser et al., 2017). DSOs, aggregators, or charging station operators can use such data models to derive all valid load profiles, which fulfil the energy service of the consumer. Next, they can select one of the valid load profiles using the flexibility potential while fulfilling the consumers demand for an energy service.

For instance, smart charging systems apply such a mechanism if they control the charging session of a BEV. The smart charging system obtains the information on how much energy needs to be charged into the BEV during the parking duration. Within these constraints, the smart charging system can derive a suitable charging schedule while fulfilling different objectives, e. g., to charge at minimal cost, minimize CO_2 emissions, or to prevent grid congestion.

In this way, BEVs could become a source of flexibility that is needed to transition energy systems towards higher sustainability while ensuring high security of supply and economic efficiency. The following chapter describes the flexibility potential of charging electric vehicles in more detail.

CHAPTER 5

SMART CHARGING FUNDAMENTALS

This chapter is based on joint work conducted by Julian Huber, Elisabeth Schaule, Dominik Jung, and Christof Weinhardt, published in *World Electric Vehicle Journal*, cited here as: Huber et al. (2019b).

Flexibility within the charging session could be a chance to overcome the challenges of the energy transition described in the previous chapters and to achieve other optimization objectives. While a grid operator can control charging to avoid grid congestion and thus expensive network expansion, an electricity supply company could use flexibility to shed consumption during price spikes or to lower balancing costs. Furthermore, charging station operators can shift the charging session towards times with lower shares of conventional generation within a generation portfolio, which can result in lower prices and CO_2 emissions during charging (Huber and Weinhardt, 2018).

To reach these objectives, smart charging systems optimize the charging session towards one or multiple objectives while reaching a desired SoC within a given time frame. The flexibility potential used by a smart charging system is illustrated in Figure 5.1. The overall flexibility in the charging session is defined by the technical boundaries that do not change over time (e. g., maximum charging power and battery size of BEV). For each charging session, only a part of this technical potential can be used. This potential can be quantified by an information system integrating information from the BEV (e. g., the initial SoC) and the user (e. g., planned parking duration).

Within these boundaries, the users of the smart charging system can decide on how much flexibility they want to offer to fulfil the objectives of the smart charging

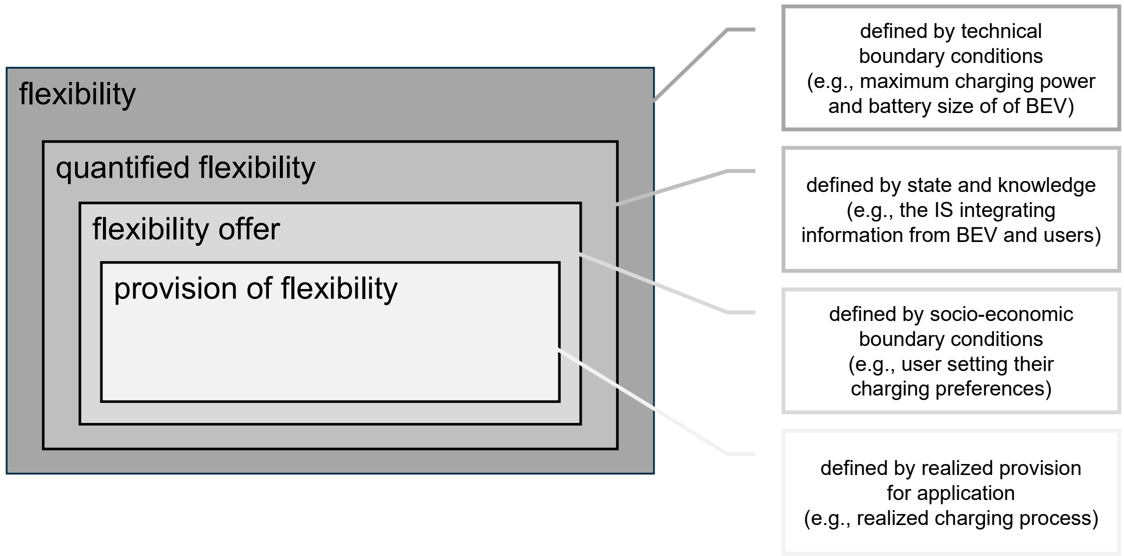

Figure 5.1.: Description of flexibility potentials from Lehmann et al. (2019) adapted for smart charging.

system. To define the flexibility offer, users could either decide between flexible and inflexible charging tariffs (self-selection) or explicitly state their charging preferences (elicitation), e. g., planned departure time and energy requirements. While a tariff selection is a discrete choice between several alternatives, an explicit input of preferences can require several decisions on different scales. This makes the decision much more complex and uncomfortable. On the other hand, the charging flexibility can be specified more precisely and less optimisation potential is lost.

How flexible users are in their decision depends on whether they accept or even foster smart charging and its objectives (Huber et al., 2019a; Will and Schuller, 2016). The flexibility offer limited by this socio-economic potential is the boundary in which smart charging systems can use flexibility to realize an optimization objective.

This chapter is structured along with the flexibility potentials in Figure 5.1. We first describe the technical boundaries for smart charging given by BEV and battery technology. Second, we analyse how smart charging systems can quantify the flexibility in individual charging sessions. Third, we discuss how users and their mobility behaviour affect the flexibility potential in smart charging. The chapter concludes with a discussion of typical objectives of smart charging systems that make use of the remaining flexibility potential.

5.1. Technology in Battery Electric Vehicles

BEVs and their battery technology provide the first technical restraints to smart charging. This section provides a summary of contemporary BEVs and their battery technology and discusses their suitability for smart charging.

Types of Battery Electric Vehicles Electric cars are automobiles in which electric motors provide the propulsion energy to the wheels. Subgroups are hybrids or hybrid electric vehicles that have two storage systems for propulsion energy. First, hybrids have a gas tank feeding an ICE or a fuel cell. Second, they have an electric rechargeable battery unit powering the electric motors. While pure hybrids only recharge during driving, e. g., by recuperating kinetic energy while slowing down, plug-in hybrids (PHEVs) can also recharge the battery system by connecting it to the electricity grid and could be used for smart charging. Full-electric vehicles (FEVs) do not have a secondary storage or conversion unit besides the battery. Table A.1, in the Appendix, shows the technical specifications of most-selling BEVs in the US in 2019. Five of them are FEV with an average battery capacity of 68 kWh. The remaining PHEVs have smaller batteries around 12.12 kWh.

As only PHEVs and FEVs charge from the electricity grid, only they can have an impact on the electricity system, e. g., by causing load peaks or providing flexibility by demand-side management measures. In consequence, in this work we focus on PHEVs and FEVs, which are both summarized by the term BEV in the following.

Because they do not burn fuel, FEVs do not emit any emissions locally (e. g., CO_2 or water), except noise and heat. The same applies to hybrid vehicles operated in full-electric mode. However, as hybrids usually have much smaller battery units, they often only have an electric range of up to 50 km (see Appendix Table A.1) and are less relevant for smart charging.

Battery Technologies The battery units in BEVs are based on different battery technologies. These technologies differ in several properties. Besides cost, energy density efficiency is one of the most important properties. Energy density efficiency quantifies how much electric energy a battery unit can store at a given volumetric size or weight. As a reference, gasohol E10, i. e., gasoline with 10-volume-% added ethanol, has a specific energy of 12,094.5 Wh/kg and an energy density of 9,216.7 Wh/L. In contrast, a Lithium-ion battery's energy density ranges around 100.00–243.06 Wh/kg and 250.00–730.56 Wh/L.

As batteries have a low energy density, FEVs require larger and heavier energy storage systems than cars with an ICE. However, this is partly compensated by the higher tank-to-wheel efficiency of FEVs. While ICE efficiency is limited by the temperature difference of the Carnot efficiency and maxes out at 25–35 %, electric power trains in FEVs can exceed 90 % tank-to-wheel efficiency (Howey et al., 2011). As cars accelerate and slow down perpetually, lower weight is usually a benefit as lower weight improves driving dynamics and reduces energy consumption and wear. In result, energy density efficiency in both weight and volume is a key factor in the selection of battery technologies.

Smart charging requires the following battery characteristics: The battery should have little self-discharging so that the battery can be charged to full SoC well before departure, e. g., when energy is available, and hold this energy until the time of departure. Next, the battery should have no memory effect, i. e., a reduction in capacity if the battery does not fully discharge before starting the next charging cycle. Using a battery with memory effect would imply that (smart) charging should be only conducted at a low SoC to retain battery life, which would reduce the potential for smart charging. Especially with vehicles-to-grid concepts (V2G), low cyclic ageing is an essential factor. With low cyclic ageing, using the BEVs battery as buffer storage would directly reduce the batteries' life expectancy.

Manzetti and Mariasiu (2015) describe the characteristics of various battery technologies in the order of increasing energy density. Lead-acid (Pb-acid) battery systems are the oldest electric energy storage technology used in cars and are commonly used as starter batteries in cars with ICE. While being inexpensive, a downside is the usage of acid substances within the car. Compared to other technologies, Nickel-Cadmium (NiCd) batteries have the upside of showing low cyclic ageing, which is a benefit in smart charging and especially V2G concepts. The characteristics of Nickel-Metal-Hydride (NiMH) batteries resemble Nickel-Cadmium. However, in comparison, they show a lower memory effect. A characteristic negative to the use of smart charging is that such batteries show a high amount of self-discharging. High self-discharging implies that the battery should be charged right before the departure of the BEV so that the driver can profit from a full SoC. While Sodium Nickel Chloride (NaNiCl) batteries can store electricity for more prolonged periods, they are linked to problems with operational safety. Lithium-ion polymer batteries show lower cyclic ageing than standard Li-ion batteries. They are well suited for both FEV and smart charging because of low cyclic ageing and showing no memory effect. Technical challenges are instability against overloading and deep discharging.

Battery Ageing in Lithium-Ion Batteries Lithium-ion polymer is the most popular battery technology in BEVs, e. g., all BEVs in Table A.1 are applied with Lithium-ion battery technology. Given the characteristics of such Lithium-ion batteries, they are well suited for storing propulsion energy in cars due to their high energy density. Lithium-ion polymer batteries also allow an interrupted charging and show no memory effect which allows to start charging sessions at different SoC levels and allows for smart charging. Still, the operation and charging behaviour of BEVs impacts the expected lifetime of Lithium-ion batteries (see e. g., Vetter et al. (2005) for a detailed description of the chemical processes leading to battery ageing).

Barré et al. (2013) differentiate between calendar [sic] and cycle [sic] ageing. Calendaric ageing describes the loss in energy capacity that is independent of the cycling of the battery, i. e., how often the battery charges and discharges. The main factor of how fast a battery's energy capacity degrades with lifetime is its temperature. In general, lower battery temperatures result in slower calendaric ageing. This ageing process is independent of the way the battery operates during smart charging.

In contrast, cyclic ageing describes all factors concerned with the use of the battery and is influenced by smart charging. In particular, the upper and lower limits in the energy capacity used for cycling and the charging current influence the cyclic ageing of Lithium-ion batteries (Fotouhi et al., 2016). Using a more extensive range of SoC and higher voltage levels to increase maximum charging power increases the flexibility in smart charging. As this has adverse effects on cyclic ageing, there are trade-offs between the usage of BEVs as demand-side management measures to provide services to the energy system and the battery lifetime of BEVs.

Battery ageing is relevant, as current discussions involve the ecological life-cycle assessment of FEVs compared to cars with ICE. Critics claim the resource-intensive production of FEV batteries and the usage of non-renewable electricity for charging FEVs have adverse effects on the environment. The results of the life-cycle assessment highly depend on the expected lifetime of the FEV. Hawkins et al. (2012) calculate that at a lifetime of 150.000 km, the climate impacts of PHEVs and FEVs are 27 % and 78 % lower compared to cars with ICE.

Charging Technology and Standardization BEVs depend on the electricity system to meet their energy demands. As the maximum charging power of BEVs is high compared to other domestic energy consumers, regulators and industry derived particular plug types (defined in IEC 62196) and communication protocols to ensure safe handling of high voltage and currents occurring with BEV charging. Conductive charging systems are the most common charging system in which a cable-plug connection transmits the electricity. In contrast, inductive or wireless charging uses electromagnetic induction to transfer energy between induction coils.

IEC 61851-1 defines four different charging modes for conductive charging systems with different voltage levels, maximum charging power, and communication capability. While Modes 1–3 operate with alternating current, Mode 4 provides direct current to the BEV. Table 5.1, adapted from Hardman et al. (2018), provides a review of charging modes defined in IEC 61851-1.

As a default, Mode 1 describes the charging of BEVs on a local household socket-outlet or a single or three-phase CEE-socket. This mode offers a simple fallback solution as a BEV with charging Mode 1 can charge at any household socket. On the downside, this mode charging mode is rather slow and cannot be used for smart charging as no communication protocol is applied. Mode 2 relies on a dedicated delivery point (socket outlet), i. e., a wall box, procuring higher maximum charging power and allowing for communication between delivery point and BEV. While Mode 2 delivery points are often installed in residential and work areas, the faster Mode 3 delivery points are mostly found in workplaces and public charging locations. The reason is that their maximum charging power exceeds the power capacity of typical residential house electricity connections. The communication protocol in Mode 3 is based on IEC 61851-1 or ISO/IEC 15118. Delivery points with Mode 4 charging provide direct current at high voltage levels up to 400 kW and are often installed along highways.

Table 5.1.: Charging nodes defined in IEC 61851-1 adapted from Hardman et al. (2018).

Charging Mode	Power [kW]	Smart Charging	Typical Location	Socket System [Outlet|Inlet]
Mode 1	1–3	No	Home	Domestic plug | Type 1/2
Mode 2	1–7	Yes	Home, Work	Domestic plug | Type 1/2
Mode 3	>43.5	Yes	Work, Public	Type 1/2 | Type 1/2
Mode 4	>400	Yes	Highway	CCS (CHAdeMO)

Quantification of Flexibility in BEV Charging BEV charging does often not require a predefined load profile but has some intrinsic flexibility. Daina et al. (2017) use a figure similar to Figure 5.2 to describe and model the flexibility in BEV charging based on charging choices of BEVs users. If the BEV users decide for a minimum SoC^d at a given deadline t^d, the charging session of BEVs is flexible as the energy demand can be fulfilled using different paths within the dotted area, starting at the time of arrival t_a. A smart charging system can realize different paths by influencing the charging power or the energy provided to or extracted from the battery.

Using the taxonomy provided by Petersen et al. (2013), the charging session of a BEV can be modelled as a battery, where a certain state of charge SoC^d must be reached within a time deadline, usually departure time t_d. The constraints of the charging session, presented in Figure 5.2, are the maximum charging power $\dot{C}$, the energy demand $SoC^d - SoC^a$, and the time available for charging $t_d - t_a$. Within these constraints (dotted area), the charging session (black line) can be optimized by smart charging systems. V2G concepts allow the discharging of the BEVs' batteries by allowing for negative charging powers, i. e., a declining black line.

Neupane et al. (2014) and Ludwig et al. (2017) use the terms time and energy flexibility to describe the flexibility in energy consumption. Energy flexibility is the potential for change in the energy consumption profile, while time flexibility is the potential for a shift of the consumption profile.

Similarly, we define time flexibility in BEV charging as the time interval of reaching the desired SoC^d at maximum charging power $\dot{C}$ compared to the planned time of departure t_d. In Figure 5.2 time flexibility begins where SoC^d would be fulfilled with uninterrupted charging. A simple metric for energy flexibility is the difference between the total energy needed at time of departure and a full SoC. There is no energy flexibility if a full battery (SoC^f) is required.

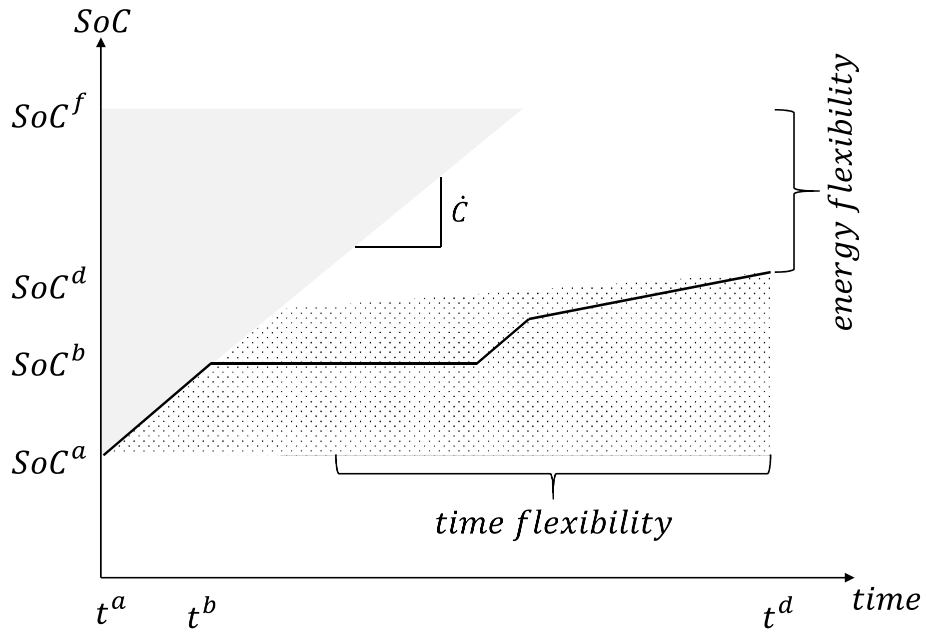

Figure 5.2.: Schema for time and energy flexibility in smart charging.

Flexibility in BEV Users' Mobility Requirements Both energy and time flexibility in BEV charging depend on the BEV users' mobility requirements. Long parking durations offer high time flexibility, while short trips rarely require full SoC and thus have high energy flexibility.

Lunz and Sauer (2015) analyse the driving behaviour of German car users based on travel logs obtained by Zumkeller et al. (2011). Drivers in this panel drive on average 36 km per day. Almost all, i. e., 95 %, trips are shorter than 42 km. For 95 % of days, the total daily trip distance is below 150 km. Consequently, Lunz and Sauer (2015) argue that if BEV users charge their BEVs overnight, a BEV with 150 km range could cover 95 % of trips of German residential car users. Adding fast recharging opportunities, i. e., >22 kW, after each trip, such a BEV could cover 99 % of total trips. This analysis shows that even with smaller battery capacities, there is flexibility potential in the charging session, as most trips are rather short compared to the parking duration of BEVs.

Quirós-Tortós et al. (2015) conduct a similar analysis of BEV charging behaviour of 221 residential BEV users in the UK. They report that users charge at full available charging power most of the time. Using the full capacity implies that no smart charging is applied yet as load shifting or curtailing would result in lower charging rates in some hours. On most days, i. e., 70 % of days, BEV users connect their BEV only once. While the first connection to the charger mostly happens at medium levels of SoC (between 25 % and 75 %), only 65 % of first connections end with a fully charged battery. In contrast, second connections result in full SoC more often.

Most residential drivers charge their BEV at home. A position paper of the German Association of the Automotive Industry (VDA, 2019) states that currently 85 % charging sessions are at private locations, i. e., residential and company parking, while only 15 % happen in publicly accessible locations. However, this share is expected to rise to 30–40 % within the next years.

Private parking locations have the most extended parking duration. Own evaluations of the German mobility panel (Zumkeller et al., 2011) show that parking locations of cars show a typical pattern through out the day. On the weekday mornings, workplaces are the most likely parking location. At workplaces, cars remain unmoved for an average of 6.2 hours. Arrivals at home peak in the early evening hours. Parking durations at home are on average 13.9 hours long. Also, they show a higher variance than parking durations at work. In contrast, parking durations at publicly accessible locations are rather short (Schmidt et al., 2020), e. g., 2.5 hours for parking at shopping locations. The highest time flexibility and potential for smart charging are found at the homes of BEV users (very long parking duration) or at workplaces (long parking duration and faster charging). The average trip distance for car trips in Germany is 36 km. At an efficiency of 20 kWh/100 km (compare Table A.1), the average residential car usage in Germany would require 7.4 kWh of electric energy. Most cars in Table A.1 show higher battery capacity letting expect a high degree of energy flexibility in BEV charging.

In summary, the current technology promises technical potential for smart charging. A comparison of battery sizes with the mobility behaviour of car users also indicates considerable potential for time and energy flexibility in BEV charging.

5.2. Smart Charging Objectives

Smart charging systems can use this flexibility potential described in the previous chapter to pursue different objectives. Consequently, there is a vast amount of literature on *smart charging*. A Google Scholar search for *'smart charging'* yields 823.000 hits as of January 2019. This dissertation aims to develop smart charging systems that meet the objectives of the BEV users and motivate them to charge flexibly. Smart charging systems ,however, will only succeed, if they also benefit their operators, which can be grid operators, power companies, and charging station operators. To analyse the overlap between the objectives of operators and BEV users (see Part III), we first identify possible objectives of smart charging systems and analyse their importance in current research.

For sorting the objectives, we rely on a concept-centric literature review approach, as proposed in Webster and Watson (2002). We search for *'Vehicle Charging* $\wedge$ *(Objective* $\vee$ *Incentive* $\vee$ *Acceptance)'* in *ACM Digital Library*, *IEEE Explore*, and *ScienceDirect*. The resulting 1.056 papers are counted in Table 5.2. The 422 matches on smart charging objectives from IEEE Explore resulted in the highest number of matching papers. Thereupon, we analysed their titles and abstracts to identify key concepts.

Table 5.2.: Matches for the search term in different literature data bases.

	Search Term Vehicle Charging $\wedge$		
	Objective	*Incentive*	*Acceptance*
ACM Digital Library	17	6	10
IEEE Explore	422	75	69
ScienceDirect	319	120	98

As expected, most papers describe the design, optimization, and scheduling of the charging sessions of electric vehicles. However, one main difference is the role and perspective of the charging system operator, who is responsible for the functionality of the smart charging system.

Perspectives on Smart Charging A first group of papers focuses on the *grid-centred* perspective of grid or system operators who centrally control the charging session of many BEVs to provide system services, optimize power flow, dispatch generation, or avoid congestion in their grid (e. g., in Mojdehi and Ghosh (2016)). Depending on the regulatory framework assumed in the paper, this can either be an integrated system operator who manages both energy generation and grid operation or grid operators solely optimizing grid operation.

The next group focuses on *market-centred* perspective of charging system operators or aggregators, who coordinate the charging sessions of multiple BEVs to optimize their outcome at market level (e. g., matching charging with an electricity product or generation portfolio or using the flexibility of the charging portfolio on reserve markets (Luo et al., 2018)).

The third group of papers is *locally centred* and aims at an operator optimizing the charging of BEVs to match consumption with a local energy resource (e. g., in Mou et al. (2015)). In this case, the BEV user often is the same entity who operates the charging station, e. g., in a residential setting where the driver integrates the BEV into the home energy management system.

Objectives of Smart Charging Systems The smart charging systems pursue different objective functions according to the charging operator's perspective. We adapt the dimensions from Sovacool et al. (2017) for a broader categorization:

Financial objective functions mainly result from a *market-centred* perspective and focus on cost advantages realized by optimized energy procurement considering benefits from the provision of ancillary services and the pricing of charging services. The charging operator can achieve financial advantages by optimizing charging in line with changing prices on the energy markets (e. g., Limmer and Dietrich 2018; Li et al. 2018). Additionally, some authors also consider using the flexibility in smart charging on frequency reserve markets (Brandt et al., 2017). One objective not mentioned by the review of García-Villalobos et al. (2014) but by Sovacool et al. (2017) is the minimization of battery degradation. As battery degradation depends on the charging strategy, some authors propose to control charging in a battery protecting manner (Schoch, 2016). Others recognize battery degradation as a constraint to be considered in economic optimization (Ortega-Vazquez, 2014). Like Sovacool et al.

(2017), we consider battery degradation to be part of the financial dimension since the battery life has a direct financial impact on the BEV owner and, unlike the other points of the technical dimension, is not related to the *grid-centred* perspective.

The technical objective functions often arise from a *grid-centred* perspective. The technical dimension sometimes affects the financial dimension, if, as in Deilami et al. (2011), an integrated system operator manages the generation dispatch and the power grid at the same time. In this case, the charging operator can obtain financial benefits from integrating BEV charging in grid operations. Smart charging can also be a tool in congestion management (Mou et al., 2015) and provide system stability in the form of different ancillary services such as frequency regulation, voltage regulation, and minimization of power loss (see Mojdehi and Ghosh (2016), Mathur et al. (2018), García-Villalobos et al. (2014), Staudt et al. (2018a)).

Flexibility in smart charging systems can also mitigate the uncertainty in wind (Huang et al., 2015) or PV (Latimier et al., 2015) generation to integrate a higher share of RES. In this way, flexibility allows to integrate more RES during charging and can help to minimize carbon emissions of the energy generation (Huber and Weinhardt, 2018). Other authors consider fairness (Limmer and Dietrich, 2018) in the scheduling of the charging loads and discuss community-based charging stations (Koutitas, 2018). Socio-environmental objectives often play a role in works with *locally centred* perspective, e. g., when focusing on the integration of local RES (Schuller et al., 2015).

Figure 5.3 shows the main objectives of smart charging systems from the perspective of the operator of the smart charging system sorted by technical, financial, and socio-environmental focus. From the perspective of BEV users, the main objective is the fulfilment of their mobility needs. For the charging system operator, the satisfaction of the drivers' mobility needs sets the constraints for the optimization in smart charging.

Trend Analysis for Smart Charging Objectives To identify smart charging objectives commonly mentioned in existing literature, we next conduct a keyword search in the abstracts of the papers found in Table 5.2. We analyse the occurrence of the keywords in the pre-processed abstracts of the initial 1.056 literature matches, i. e., removing punctuation, lower casing, and stemming. First, we generate a list of

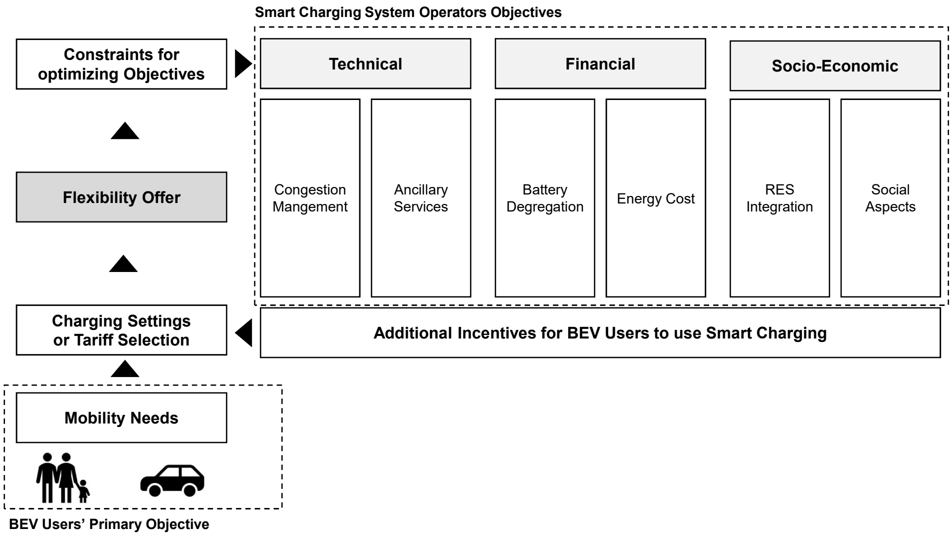

Figure 5.3.: Objectives of smart charging system operators and BEV users.

indicator keywords by screening the most common words, i. e., occurring more than 40 times, in the combined abstracts and assigning them, if relevant, to one of the optimization objectives. Table B.1 in the appendix lists the resulting keywords for different charging objectives.

We assume that the occurrence of a keyword indicates, whether or not the paper considers a given objective, e. g., a paper containing the words *'lifetime', degradation',* or *'ageing'* is likely to contain a link to battery degradation within the smart charging system. We conduct an automated search through the titles and abstracts in the initial 1.056 results. We discard all articles not containing any of the keywords as irrelevant for the further analysis.

Table B.2 in the apendix shows the resulting data structure after the literature screening. As an example, it holds the three most cited articles found in the 924 remaining results. The first paper, Deilami et al. (2011), proposes a real-time co-ordination mechanism to control multiple BEVs charging to minimize generation costs and grid losses. Besides, ancillary services (i. e., minimization of grid losses), the keyword indicator also recognizes the objective of cost minimization (i. e., the generation costs). The second paper (Sortomme et al., 2011) only classifies in the group considering ancillary services. Indeed, the paper describes the coordination of electric vehicles to minimize distribution system losses. The third paper (Gan et al., 2013) use a decentralized algorithm to coordinate charging between a utility company and car users. The algorithm shifts the charging loads to fill the valleys to avoid congestion.

Figure 5.4 plots the frequency for different objectives in relation to the publication date. Many papers assume the existence of an integrated system operator who is concerned with both a *grid* and a *market-centred* perspective. Consequently, such articles often consider more than one objective in smart charging (i. e., generation cost reduction and congestion management). Out of 511 papers with abstracts that include keywords for energy costs, 423 also contain a keyword from another objective. In doing so, financial optimization is often the main objective (e. g., if charging flexibility is used to minimize the costs of generation and line losses). Aligning consumption with the generation from RES can also reduce costs. In result, a combination of energy costs and RES integration also emerges quite frequently (221 times). Congestion management and other ancillary services are mentioned at a similar frequency. Fewer papers address keywords describing battery degradation (<20 %) or social aspects (<7 %) in their abstracts.

As illustrated in Figure 5.4, there is a rising interest in all topics over time. Although the earliest paper mentioning scheduled charging of BEVs within our search origins from 1980 (Schallenberg, 1980), a broader discussion of smart charging does not arise before 2008. In these years, the first serial production BEVs with Lithium-ion battery systems (e. g., *Tesla Roadster*) came to market and spiked a new interest in research on BEVs and smart charging. There is no clear trend for different objectives over time.

Given the current BEV, battery, and charger technology, BEVs are a promising source of flexibility for the electricity system. Time and energy flexibility are useful concepts to quantify the amount of flexibility in each charging session. In the end, BEV users are to decide how much flexibility they want to offer in different situations and for different objectives. Literature focuses on operators of smart charging systems with technical objective functions that can alleviate the challenges discussed in Chapter 4 (i. e., congestion management and ancillary services). While these are essential topics from a *grid-centred* perspective, it is unclear whether BEV users will fancy smart charging systems that focus solely on these objectives. Energy cost and RES integration are other common objectives that seem more likely to offer incen-

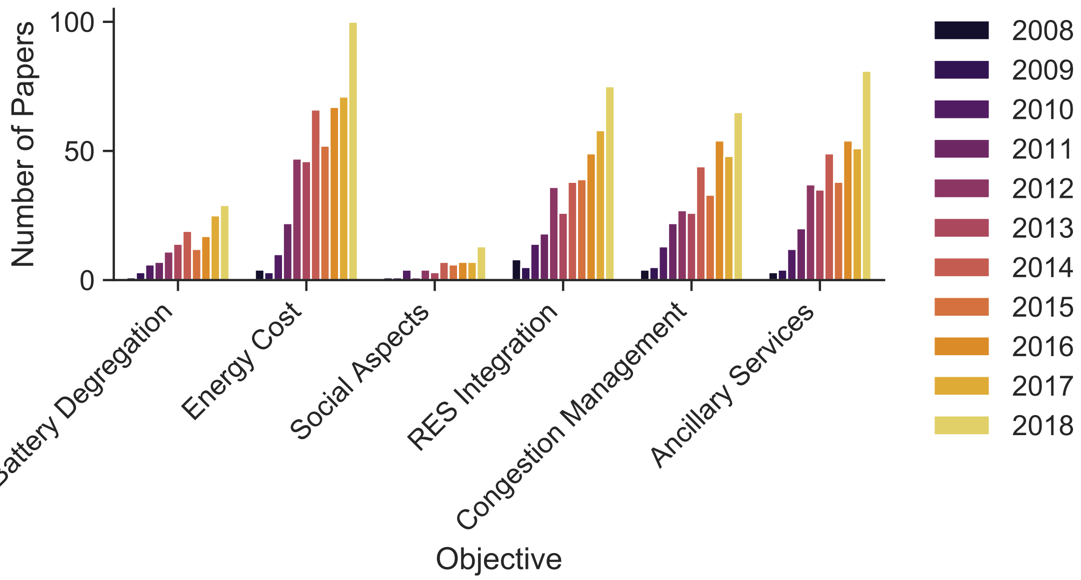

Figure 5.4.: Occurrence of smart charging objectives in the literature from 2008 to 2018.

tives to BEV users to charge flexibly. BEV users might also be motivated by slowing down battery degradation and social aspects. Such objectives, however, are little discussed in the literature. Chapter 8 provides an in-depth discussion on how the objectives of charging system operators fit the objectives of BEV users.

CHAPTER 6

SHORT-TERM FORECASTING

The optimization of BEV charging towards different objectives requires foresight of the charging flexibility and other variables connected to the charging process. The next chapter describes how short-term forecasting can use historical insights to generate predictions on future events. The frameworks and insights from this section are the foundation for the forecast used to answer RQ 5, 6 and 7. A more detailed description of the accuracy measures and forecasters used for the specific use cases is described in Chapter 10 and 11.

Reaching smart charging objectives relies on the knowledge of the charging session' flexibility and the future developments of external factors that influence reaching the target objective. As an alternative to BEV users entering the charging settings into the user interface or using defaults, smart charging systems can use short-term forecasts to estimate charging flexibility. Smart charging systems often aim to fulfil objectives that include unknown variables, e. g., when optimizing against future energy prices. As the realisations of these variables are nor available beforehand, forecasts are a crucial input to smart charging systems. This chapter provides a concise overview of the basics of short-term forecasting in the energy domain.

While forecasts are mere statements about future developments, a quantitative forecast assigns a numerical value to a predicted variable Y at a certain point in time t. Hyndman and Athanasopoulos (2018) name two requirements to derive meaningful quantitative forecasts. Statistical information about the past and the reasonable assumption that the historical patterns will continue in the future. Forecasters (also forecasting models) F serve to track these patterns and project them into the future.

Information about the past is usually stored in time series. Time series assign numerical values of a variable to specific points in time. The time steps between the individual observations can be constant or variable (Hyndman and Athanasopoulos, 2018). In time series with constant time steps, the width of a time step $\bar{t}$ is called its temporal resolution.

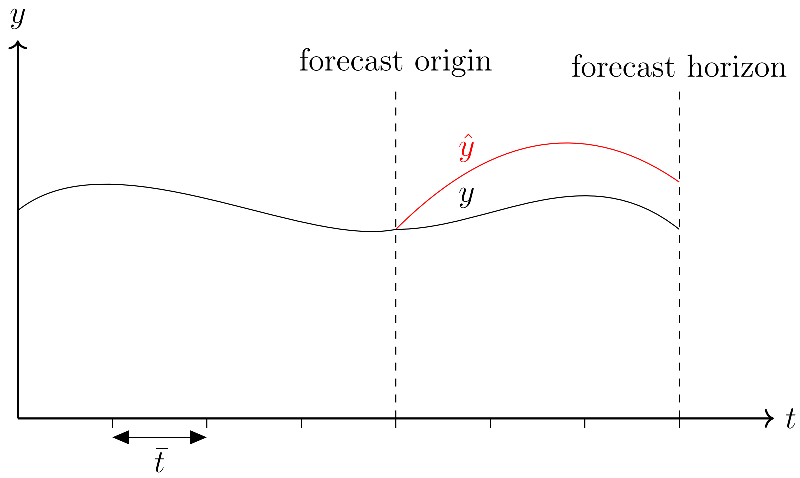

Figure 6.1.: Terminology of time series forecasting.

Figure 6.1 illustrates the forecast of a time series. During the training period (solid line left to the forecasting origin), the forecaster is calibrated using the existing data from the past to learn historical patterns of the predicted variable y_t for time t. The actual forecast $\hat{y}_t$ begins with the forecasting origin and extends over the forecasting horizon (dashed line). In this phase, the trained (calibrated) forecaster provides a forecast for the future values of the time series. In the following, this dissertation marks predicted values of a random variable Y at time t as $\hat{y}_t$. The forecaster, hereby, often relies on a set of features τ that have some predictive power on the predicted variable y. Features can be prior observations of the predicted variable or external explanatory variables (see Section 6.2):

$$F : \tau \rightarrow \hat{y}. \tag{6.1}$$

In contrast to point forecasting, in probabilistic forecasting a forecaster (model) F does not aim to predict a single value $\hat{y}_t$, but the distribution of the predicted value $\hat{P}(Y < y_t)$:

$$F : \tau \rightarrow \hat{P}(Y < y_t). \tag{6.2}$$

While some forecasters are capable of predicting the full probability distribution, e. g., kernel density estimators (Jeon and Taylor, 2012), other forecasters, e. g., quantile regression (Koenker and Bassett, 1978), do not predict a complete probability distribution $P(Y < y)$. Instead, they predict a selected set of quantiles Q. A real number q_a is an a-quantile of P if

$$P((-\infty, q_a]) \geq a \text{ and } P([q_a, +\infty)) \geq 1 - a. \tag{6.3}$$

Comparing the results of forecasters providing a full probability distribution with quantile forecast, requires the probability distribution to be discretized into the same quantiles. Besides, using discrete quantiles of the distribution makes it easier to visualize and communicate the results resulting in many papers analysing quantile predictions. In consequence, the terms quantile and probabilistic forecasting are often used interchangeably.

6.1. Forecasting Process

The forecasting process to derive predictions of a random variable comprises five consecutive steps (Hyndman and Athanasopoulos, 2018). First, the developer of the forecaster has to define the purpose of the forecast by understanding the use case of the forecast and obtaining domain knowledge regarding the problem. This step could result in technical requirements of the forecast (e. g., predicted variable, forecasting horizon, forecasting origin, and the temporal resolution of the forecast). Besides, the first step includes collecting a pool of data that could influence the predicted variable. To obtain this knowledge, the forecaster could screen literature or consult with domain experts and the future users of the forecast results. Diligent problem definition in the first step ensures that the forecast meets all requirements, uses all available information, and can later be integrated into an information system in a useful way.

In the second step, the developer of the forecaster gathers all information available to improve the forecast. The information can be statistical data (i. e., time series of the predicted and explanatory variables) and domain knowledge of their correlations. This step can build on interviews with domain experts or on literature survey.

The third step is a preliminary (exploratory) analysis of the statistical data. This step allows to identify outliers in the data and cleanse the data if necessary. Next, the preliminary analysis should identify existing patterns, correlation, trends, seasonalities, and cycles in the statistical data. These patterns provide clues for the selection and design of forecasters in the next step.

Based on the statistical data collected in Step 2 and the insights of Step 3, the fourth step is to identify promising forecasters to predict the predicted variable. Forecasters are models that use the data of a training set (see Chapter 6.4) to learn relationships between the predicted and explanatory variables. During training, the parameters or weights of the forecasters are adjusted to minimize the forecasting error (see Chapter 6.3). Usually, several forecasters are trained and compared at the same time. The comparison of the different models takes place on unseen data (i. e., validation set). This comparison allows selecting the most promising forecaster to use for future application.

The final step is to test the selected forecaster's performance under practical conditions using a suitable accuracy measure or a case study. This final step uses another set of unseen data (i. e., test set). Standard measures for the performance of a forecaster are forecasting accuracy, computing time, and other metrics such as the forecaster's performance in a use case. It is best practice, to compare the performance of the selected forecaster with an existing benchmark model (vom Scheidt et al., 2020).

6.2. Forecasters

The core of a quantitative forecast is the forecaster. Forecasters are rules, functions, or models that describe a relationship between data observed in the past and the future values of the predicted variable. Depending on the data used to model this relationship, literature differentiates different types of forecasters based on what kind of features τ are used to derive the forecast.

Time series models use only the information of the predicted variable and no external information. As they infer a regression between past and future observations of the predicted variable, they are also called autoregressive models. Such autoregressive models explain the future development of the time series based on historical patterns (i. e., trends, seasonality, cycles). Hence, they integrate prior observations of the predicted variable (i. e., lagged variables). Examples of such forecasters are linear autoregressive models, autoregressive-integrated-moving-average models (ARIMA), or exponential smoothing (Hyndman and Athanasopoulos, 2018). Time series models have the form of:

$$\hat{y}_t = f(y_{t-1}, y_{t-2}, ...). \tag{6.4}$$

When predicting values of a forecasting horizon further than one time step, not all historical values considered in the model might be available at the forecasting origin. In this case, the forecaster can include prior forecasts of the predicted variable to replace the missing observations:

$$\hat{y}_t = f(\hat{y}_{t-1}, y_{t-2}, ...). \tag{6.5}$$

Often, other variables are causally or correlatively related with the predicted variable (e. g., electricity consumption and ambient temperature). If this information is available at the forecasting origin, this information can be used as an explanatory variable x_t . Like autoregressive variable, external explanatory variables can have a time lag (e. g., z_{t-1}). Typically, regression models are used for this purpose:

$$\hat{y}_t = f(x_t, z_{t-1}, ...). \tag{6.6}$$

Mixed models take into account both explanatory and lagged variables of the predicted variable(Hyndman and Athanasopoulos, 2018):

$$\hat{y}_t = f(y_{t-1}, x_t, z_{t-1}, ...). \tag{6.7}$$

A priori it is often unclear which approach (autoregressive, external, or mixed) will result in the highest forecasting accuracy. Comparing different models with different input feature sets allows finding the best forecaster. As linear regression models and artificial neural networks (ANN) can be used for all three approaches, they are a common choice when testing the effects of autoregressive, external, or mixed input features. Comparing the accuracy of different forecasters requires an accuracy measure to quantify their accuracy. Such accuracy measures are described in the next section.

6.3. Accuracy Measures

Accuracy measures allow quantifying the accuracy of a forecast. In particular, they are used to compare different forecasters to select the best-suited for the particular use case. Besides, accuracy measures can be used as optimization criteria during the training of a forecaster.

Accuracy measures for point forecasts are usually based on the forecasting error of the individual points in time $y_t - \hat{y}_t$. The most commonly used accuracy measures in science and practice are the mean absolute percentage error (MAPE) and the root mean squared error (RMSE) (Armstrong, 2001) which has not changed during the last twenty years for the energy domain (vom Scheidt et al., 2020).

The RMSE puts higher weights on observations with larger forecasting errors. As large forecasting errors can have greater negative effects in practice, this behaviour is desired in many use cases. However, this sensitivity extends not only to poor forecasts but also to errors in the data (Armstrong, 2001). The RMSE for n points in time is calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{6.8}$$

As the RMSE is affected by the scale of the actual observations it is not possible to compare forecast accuracy between different data sets with different scales (e. g., load forecasts on substation and energy system level). In contrast, scaled accuracy measures are more comparable between different data sets, as they set the forecasting error in relation to the height of the observation.

The mean absolute percentage error (MAPE) is a scaled accuracy measure that builds on the mean absolute error (MAE). The MAPE indicates the average percentage deviation of the forecast from the actual observation which makes it easy to communicate:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i}| \times 100\%. \quad (6.9)$$

While the MAPE is independent of the scale of the data set, is not suited for all data sets, as it inflates with small actual observations (i. e., low magnitude of the data set) and is undefined if the actual observation is zero. This is particularly relevant in the energy domain, as generation, consumption, and prices can assume negative and zero values. Besides, MAPE is biased accuracy measure as it favours low forecast for positive data sets.

Selecting accuracy measures is a trade-off between the following properties (Armstrong, 2001). First, accuracy measures should not be affected by the scale of the data set to allow for comparisons between different use cases and time series. However, accuracy measures must also fit the specific use case and provide face validity to experts who are users of the forecast. In addition, new accuracy measures should provide similar results to existing ones to ensure construct validity. In some use cases, having few large forecasting errors is worse than having many small ones. In this case, an accuracy measure which is sensitive to outliers (e. g., RMSE) would be more valid than a less sensitive one. However, in most cases, insensitivity towards outliers is a desired property when evaluating forecasting results. One way to obtain insensitive accuracy measures is by using the median instead of the mean when averaging individual observations. Last, accuracy should not be biased (see above) and independent of the difficulty of the forecasting task.

An in-dept discussion on how different accuracy measures manage to trade off between these properties is described in Hyndman and Koehler (2006) and Granger and Pesaran (2000). For probabilistic forecasts, the accuracy of the predicted distribution $\hat{P}(Y < y_t)$ has to be evaluated against the actual observation y_t. This leads to additional requirements on accuracy measures. Gneiting and Raftery (2007) discuss these requirements and propose accuracy measures for probabilistic forecasts.

6.4. Out-of-Sample Validation

Out-of-sample validation allows measuring the forecast accuracy under realistic conditions on unseen data (i. e., on a test set). Out-of-sample validation is not only required when testing the final model in Step 5 but also in Step 4 during model development when multiple forecasters are trained on the training set and compared with each other. An additional hold-out-sample (i. e., validation set) during training can be used to avoid over-fitting (Armstrong, 2001). Over-fitting means that a model is to well adapt to the training data which bears the risk of not generalizing to other data. Hence, data is usually split into training, validation, and test set.

The splitting ratio of these three data sets depends on the data available and further considerations. For instance, machine learning models often require a large minimum amount of training data to achieve acceptable results. This need for data would require a relatively large share of data for training if the total data is limited. To overcome such problems, there exist different approaches to out-of-sample validation which are described in the following. The following paragraph describes out-of-sample validation with only two data sets (training and test) to ensure clarity. The simplest form of out-of-sample validation is splitting the data arbitrarily into training and test data. However, splitting only once can, by chance, result in splits where the characteristics of training and test set are non-representative. This problem can be mitigated through cross-validation. Cross-validation is the idea to perform multiple splits and evaluations on the available data to average out such situations and make use of all data available and thus increase validity of results.

Exhaustive cross-validation splits the data set into all possible combinations of training and test set. This exploits the full potential of existing training data and ensures a forecaster that could generalize on data that is similar to the data set. Exhaustive cross-validation is often used when analysing non-time series data. Leave-one-out cross-validation uses a single point of the data of size of N as a test set (Webb, 2003). Subsequently, N models are trained on a training set of length $N-1$ and their performance is evaluated on a test set of length one. In time series, this only works for a forecasting-horizon of one. For forecasts with a forecasting horizon greater than one time step, the length of these segments is not one but must correspond to the forecasting horizon. The leave-p-out approach includes p segments in the test and $N-p$ in the training set. This results in an even higher number of combinations of training and test sets.

Depending on the initial amount of data the high number of combinations can be computationally expensive. Non-exhaustive cross-validation restrains from using all possible combinations as a more economical alternative. The k-fold approach splits the data into k areas of equal size. In time series forecasting, the length of these areas corresponds to the forecasting horizon. Each range is used once as a validation set and $k-1$ times as part of the training set. This reduces the calculation effort compared to a complete cross-validation. For the special case $k = N$ the k-fold approach corresponds to the leave-one-out approach.

Another approach to incomplete cross-validation is bootstrapping. Here individual observations are randomly assigned to the training or test set over multiple cross-validation runs (Efron and Tibshirani, 1994). In contrast to k-fold, the data of the test set are scattered over the entire data set, which can allow to capture all features of a time series with each run (fold). On the downside, the assignment is naturally random and not controllable (Kohavi, 1995).
It is generally accepted that cross-validation is preferable to the use of a single hold-out (Blum et al., 1999). Full cross-validation can quickly become very computationally intensive and can have practical limitations. In this case, incomplete cross-validation can be used.

Figure 6.2 describes a prototypical data split for model fitting, model selection, and out-of-sample testing. The first step is to remove a test set from the initial data. This test is used as a hold-out sample for testing the forecasters' performance under realistic conditions and is not used during model development in Steps 1 to 4. Next, the remaining data is used for model selection and split into training and validation set. In Figure 6.2 this is performed in an outer cross-validation loop using a five-fold cross-validation. The forecasters are trained and compared on five different data splits. During training, some forecasters might require an inner cross-validation loop to find model parameters or prevent over-fitting. In the example, this is implemented as incomplete cross-validation with two folds.

This example shows, that most forecasting task require multiple data splits and can apply different approaches to split the data. In the case of a time series forecast, many cross-validation methods have a decisive weakness. Sampling from the initial data set can break the temporal integrity of training, validation, and test set (Arlot et al., 2010). If the patterns are constant throughout the time series, putting the training set before the validation before the test set mimics the practical application of the forecast as only past data is used to forecast the future. However, this might

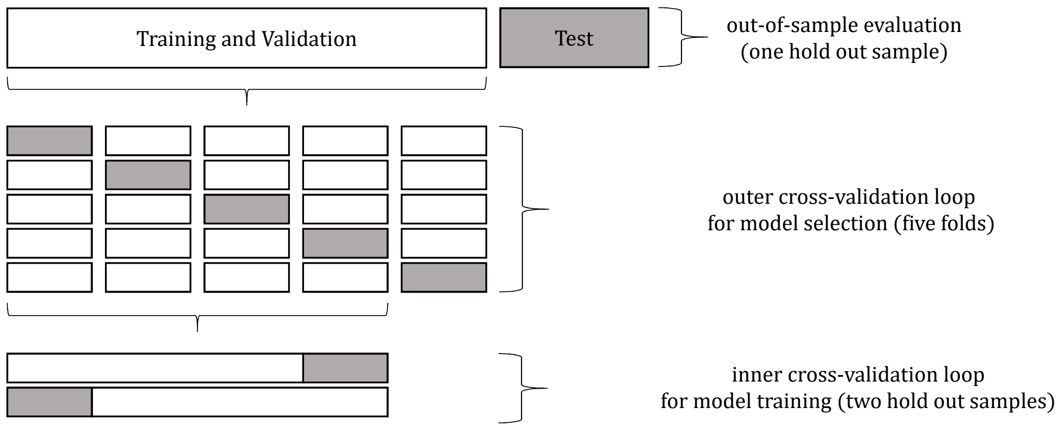

Figure 6.2.: Out-of-Sample validation for model fitting, model selection, and out-of-sample testing.

not work when only limited (e. g., one year of) data is available. For instance, with a split which keeps the temporal integrity, the training would take place in the first half of the year, the models would be selected over the late summer and tested in autumn and winter. Such a forecasting process would not lead to satisfactory results as the forecaster could not learn the seasonal patterns. In contrast, breaking the temporal integrity would allow ensuring that each of the three data sets contains a representative selection of the data available in the time series.

To keep temporal integrity, forecasting often either splits the data into three simple hold-out samples (training, validation, test) or uses a rolling window approach of cross-validation. In both cases, often two steps are applied (Hong, 2010). First, the first 50 % of data is used for training and the following 25 % is used as a validation set for model selection. Second, the selected model is retrained on the joint training and validation set and testes on the remaining 25 % of data. With this approach only the last 25 % of data are used for testing. To include a lager part of data into the test set, the rolling window approach starts with a smaller training and validation set and moves forward in time.

Figure 6.3 shows how the rolling windows approach would split the initial data set compared to five-fold cross-validation. It is evident, that the rolling windows approach does not include data from all over the time series into the test set. Another drawback from splitting data this way is that many standard implementations

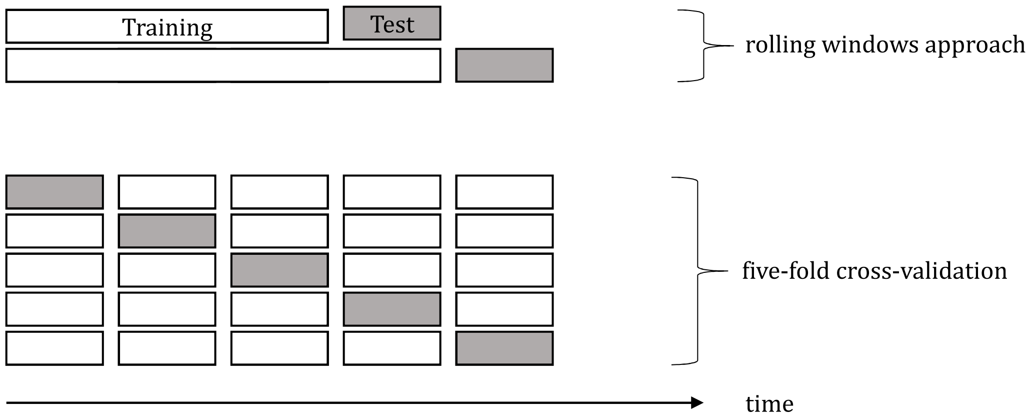

Figure 6.3.: Comparison of of five-fold cross-validation and rolling window approach for out-of-sample testing in time series.

for machine learning do provide frameworks for standard cross-validation, but not for rolling window cross-validation with time series. Hence, many researchers use other cross-validation approaches for time series forecasting. While this breaks the temporal integrity of the data, it usually has no adverse effects in practice. Bergmeir and Benítez (2012) investigate the effect of using conventional cross-validation methods compared to the rolling window approach in an empirical study. Although the cross-validation breaks the temporal integrity (i. e., using data behind the test set for training) they could not find any practical disadvantages of model selection using cross-validation. On the contrary, the rolling window approach even achieved less robust accuracy measures. Subsequently, it is recommended to use a blocked form of cross-validation (i. e., k-fold) in forecasting tasks.

CHAPTER 7

DIGITAL NUDGING

With advances in behavioural economics, predictions of human behaviour in certain decision situations become more accurate. In particular, behavioural economics finds that human behaviour is not only driven by financial incentives and rational decision making (Tversky and Kahneman, 1974). Choice architecture is the idea that thoughtful design of decision environments can use this knowledge to nudge decision-makers towards desirable outcomes without adding substantial financial incentives (Thaler and Sunstein, 2009). Choice architecture could allow information systems to change social norms towards more sustainable behaviour (Watson et al., 2010). A point of vantage is the interaction of consumers (e. g., BEV users) with the information system (e. g., user interface of a smart charging system). Here, the users' interaction with the energy system (e. g., their charging settings) depends on the design of the information system. The following chapter lays the groundwork for the application of choice architecture in smart charging by introducing digital nudging and its analogous roots in Section 7.2 and 7.1. Finally, it provides an overview of design aspects for digital nudges and a methodology for developing and testing digital nudges in Section 7.4 that is applied in Part III of this dissertation.

7.1. Choice Architecture

In contrast to homo oeconomicus, regular people tend to make irrational decisions. They smoke, eat unhealthy food, or save too little for retirement. They do not always maximize their overall utility since their rationality is limited by cognitive limitations and influenced by heuristics (Simon, 1955).

For instance, Tversky and Kahneman (1979) find that individuals consistently prefer guaranteed payouts to lotteries with the same expected payout as they are risk-averse. This effect goes so far that the experiment participants do not maximize expected economic outcome but show a concave utility function for gains. Tversky and Kahneman (1979) explain this deviation from the rational choice with a set of heuristics in human decision making that bias the rational choice.

In this way, biases can lead to decisions that do not yield the best result for the decision-maker. The decision environment strongly influences the outcome of the decision-making process. For instance, the positioning of dishes on display in a canteen affects the choice of customers. Customers are more likely to pick fruits if presented at eye level (Thaler and Sunstein, 2009). Choice Architecture is the conscious design of decision environments. Since heuristics and biases influence human decisions (Tversky and Kahneman, 1974) choice architects can use this knowledge to nudge people towards better decisions. A nudge is a way of directing people's behaviour in a particular direction without limiting freedom of choice or fundamentally changing economic incentives, e. g., by adding monetary incentives. Thaler and Sunstein (2009) propose using nudges as a policy tool and call the concept *libertarian paternalism*: This assumes that private and public institutions may influence people through nudges if their freedom of choice is respected. Thaler and Sunstein (2009) describe a series of nudges and give vivid examples.

Setting defaults takes advantage of people's inertia in the decision making process. People tend not to change decisions once taken, which could be due to laziness or fear of change (Jung and Weinhardt, 2018). In result, countries which have an opt-in for organ donation receive a rate of organ donors that is below the general consent rate in surveys. Countries implementing consent as default and an opt-out option have a significantly higher quota of organ donors (Whyte et al., 2012).

Choice architecture should also expect human error and take precautions to prevent it. For example, diesel nozzles are too large to fit into gas tanks to avoid filling gas tanks with diesel (Thaler and Sunstein, 2009).

Pronounced feedback helps people to understand their decisions better and adapt their actions accordingly. People consume less energy when they receive real-time feedback on their consumption (Tiefenbeck et al., 2019). Feedback can involve gamification aspects. For instance, the user interface of the latest model of the BEV

Nissan Leaf presents a growing tree as long the driver stays in the energy-saving eco-mode (Yoshizawa et al., 2011).

In giving feedback, choice architects must understand mappings that users make when considering decisions. Staying in the energy domain, most users will not have a mental representation of CO_2 saving equivalents expressed in a unit of mass. However, translating the mass of CO_2 into the distance travelled by car, emitting the same amount of CO_2 will give them a more vivid image (Thaler and Sunstein, 2009). Structuring complex choices can make choices more accessible.

Last, prices or vouchers can also be considered a nudge as long as they do not substantially change the economic incentives (Thaler and Sunstein, 2009), e. g., setting a price tag at 99 instead of 100 €.

While every decision is a possibility for choice architects' intervention, digital (choice) environments increasingly affect real-world behaviour. Weinmann et al. (2016) transfer the concept of nudging in the domain of human-computer interaction: digital nudging uses insights from behavioural economics to design information systems in a way that nudges users' decisions. The next section describes how nudges are used for environmental protection and in information systems.

7.2. Digital Nudging

Nudging finds a wide application in the design of digital settings. Weinmann et al. (2016) define digital nudging as *'the use of user interface design elements to guide people's choices or influence users' inputs in online decision environments'*. Meske and Potthoff (2017) list the following set of nudges applicable in user interfaces. We expanded this list by providing a description with examples for applications:

- Anchoring - Tversky and Kahneman (1974) show that decision-makers are influenced by initial pieces of information, even if they are unrelated to the task at hand or stay with pre-selected anchors. For instance, a high initial slider position can nudge people to select higher values when offsetting CO_2 compensations for air travel (Székely et al., 2016).

- Customized information - Individual differences in users might cause them to react differently to elements in the user interface. An adaptable system could offer information tailored for the users' to nudge them towards intended goals, e. g., by offering adaptive nudges that consider user characteristics (Hummel et al., 2017).

- Decision staging – A choice architect can break down complex decision into multiple steps, e. g., by spreading the decisions in multiple frames of a web page. Breaking-down the decision can facilitate the decision for users who would otherwise be overwhelmed with the complexity of the decision, e. g., when selecting privacy setting (Kroll and Stieglitz, 2019). More, decision station can set anchors and provide framing that affect the decision making directly.
- Informing - Information is another way of providing context to a decision situation, e. g., by providing feedback on the (expected) outcome of the decision. (Tiefenbeck et al., 2019) find that providing feedback on energy consumption can influence consumption behaviour.
- Simplification of feedback – Simplification can address the decision environment (see decision staging) but also the provision of feedback. Simplified feedback allows users to map decision outcomes towards ideas that are meaningful to them. For instance, while avoided emission communicated as tons of CO_2 are less intuitive, converting this information into km driven by an ICE car might be more accessible to the users (Thaler and Sunstein, 2009).
- Default setting - Initial slider positions and pre-checked checkboxes can utilize decision inertia so that the users are more likely to stay with the pre-selected option. This nudge is so powerful that the Court of Justice of the European Union (2020) issued a ruling that pre-checked checkboxes are not valid to obtain consent in some settings.
- Time limitations - In some cases, users procrastinate decisions and interactions with the information system. In such cases, a time constraint (e. g., countdown) can incentive the users to take action. This is mostly known from online shops, where special discounts are only provided for a limited time frame (Djurica and Figl, 2017). Roth and Ockenfels (2002) find that time limits alter users' behaviour on eBay and Amazon.

- Precommitment - Holding people up to their targets is a powerful tool to overcome other biases, that might lead them astray from fulfilling their goal. Already in the 1970s energy crisi, Becker (1978) shows how goal setting can help users to reduce energy consumption in their homes. This step can be aided by information systems (Loock et al., 2013b).

- Social influence - As the behaviour of their peers influences humans, information about normative behaviour or scoreboards can nudge them into the direction of the socially promoted behaviour, e. g., when feedback on energy conservation is shared with peers (McCalley and Midden, 2002).

- Reminders and Warnings – Reminders and warnings are simple user interface elements, that request users to take action and direct their decision making.

- Framing - Framing uses the words for descriptions or texts to change the context of a decision situation. A typical example is loss framing, resulting in survey participants being more likely to give up self-harming behaviour (e. g., smoking) when they are informed about the adverse effects of continuing smoking than the benefits of giving up (Schneider et al., 2001).

As this list is not comprehensive, it provides an overview on how digital nudging can foster more sustainable behaviour. Further taxonomies for nudging interventions are discussed in Section 7.4. Which of these digital nudges can effectively alter users behaviour depends on the context of the decision situation. Many everyday decisions affect our environment. The next section describes how nudges can help to foster sustainable behaviour in such situations.

7.3. Digital Nudging and Environmental Protection

Research shows that digital and analogue nudges successfully get people to behave better in their interest or for the benefit of society and the environment. In particular, nudges are successful in promoting sustainable behaviour. This section summarizes findings on the successful use of nudges towards sustainable behaviour and discusses (digital) nudges in the field of information systems research.

Nayar (2017) identify a gap between public awareness of water scarcity and actual action on the problem. The authors use choice architecture to close this gap. As nudges, they use a personal approach, information cards (with a social nudge – reporting positive acts of peers – and action points to save water) and reminder stickers. In a field test with 615 households in rural India, they found water savings of 10.3 % compared to the control group of 150 families. This result shows that even inexpensive measures can lead to significant effects on behaviour, if they are designed carefully.

Schultz et al. (2007) show that normative messages (i. e., a social nudge) can also affect energy consumption. In a field study, they investigate the electricity consumption of 290 households in the US. Based on the consumption data, households receive feedback on their electricity consumption. The letter includes information on whether their average household consumption was below or above that of the peer group. Besides, the information for half of the households included an injunctive message (i. e., a positive or negative emoticon). On average, households with consumption above the average consequently reduced their electricity consumption. Households with below-average consumption and without an injunctive message experienced a boomerang effect: they significantly increased their electricity consumption. This effect did not occur for peers that received an injunctive message (i. e., a happy smile). This result shows the constructive and destructive power of social nudges and normative framing. However, prudent design can counteract unwanted adverse effects.

In a field trial with 118 households, over 100 days Asensio and Delmas (2016) found that framing energy conservation, as a health issue in the community is more effective and sustainable than a monetary reward. They sent treatment messages to households, comparing their consumption of the last two weeks with the neighbourhood average. The message also stated the amount of air pollutants saved or emitted compared to the average. Besides, the message noted that air pollutants *'contribute to known health impacts such as childhood asthma and cancer'*. The control group received a similar message, which also included a comparison of consumption with the neighbourhood and the money saved or spent compared to the average household. The results show that the health framework reduces energy consumption by 8-10 % compared to the control group. This result indicates that framing can be a successful nudge that can complement social nudges and promote long-term behavioural changes towards sustainability.

Another field of application are contracts for electricity from RES where Momsen and Stoerk (2014) tested the effectiveness of several digital nudges with deviating success. Similar to Nayar (2017), they find a gap between intention and action for the signing of such energy contracts: 50-90 % of Europeans prefer energy from RES and are willing to pay a small premium for it (similar numbers are found in Germany by Mengelkamp et al. (2019)). Nevertheless, less than 3 % had such a contract in 2014. An online experiment examines whether digital nudges can close this gap. The authors emulate the website of an electricity provider and simulate the closing of a contract. The different mock-ups of the website implement the following digital nudges based on priming, mental accounting, framing, decoy, social norms, and a default, where the renewable contract is pre-selected. Only the default nudge shows a significant influence on the choice. It increases the proportion of test subjects voting for the renewable contract by 44.6 %. Here nudges are implemented within a digital decision environment and tested in an experimental setting. The authors admit that the observed effect strengths are not necessarily transferable to the field. However, it should be possible to conclude the direction of the effect.

In another example for the digital nudges in information systems, Loock et al. (2013a) provide an overview of information-system-based feedback interventions to save electricity, gas, or fuel. The authors also test how target setting (i. e., stating how much energy one wants to consume) influences the future power consumption and analyse the effect of default goals within this process. The evaluation takes place on a web portal with 1,791 users. The results show that pre-selected default targets significantly influence self-defined targets. However, if the defaults are too high or too low, they lose their effect.

Choice architect must further consider the target group of the intervention. Costa and Kahn (2013) show that nudges work differently with different target groups. As described in several studies above, households receive information about their energy consumption and that of their peers. The authors find that this nudge is four times more effective with political liberals than with conservatives. This result shows that nudges should not only use the basic human behaviour patterns (e. g., biases) but should be tailored to the user group and their goals.

These examples from literature show that nudges (especially defaults, framing, and social nudges) are a powerful tool to foster environmental friendly behaviour. However, nudges must fit the context and the targeted user group, as otherwise, they can backfire and even have adverse effects.

7.4. Digital Nudge Development

While the previous chapter shows that nudges are a promising tool to foster environmentally friendly behaviour, not all nudges work successfully for each user group and decision situation. To develop fitting digital nudges to a specific decision situation Mirsch et al. (2017) describe a five-step nudge development process based on Weinmann et al. (2016). Schneider et al. (2018) integrate two of these steps to create a four-step process. These digital nudge development processes rely on analogous processes for the development of nudges and behaviour change interventions in offline settings (Datta and Mullainathan, 2014; Ly et al., 2013). In the following, we describe the digital nudge development process based on Schneider et al. (2018) and indicate the respective steps from Mirsch et al. (2017) in parentheses.

Step 1: Define the goal (define) The first step in nudge development is to define the goal of the behaviour change intervention. This goal has to be aligned with the users' goals, the organisation providing the information system, and society. For instance, charging station operators might want users to charge more flexible to optimise energy procurement. In contrast, BEV users want to charge fast and the reliably with green electricity. At the same time, society aims for high shares of RES, which requires a flexible demand-side, to obtain overall sustainability goals. These goals influence the choices available, which affect the design of the choice menu. For instance, a smart charging station could let users decide on how flexible they what to charge their BEV. The characteristics of choice determine what ways the choice architect can go in Step 3. The smart charging system could either offer a binary decision between a flexible and inflexible charging tariff or ask the users to explicitly set planned departure time and energy requirement on two (continuous) scales. The resulting choice menu affects what types of digital nudges can be used to change the users' behaviour.

Step 2: Understand the users (diagnose) Most nudges exploit or correct peoples' biases. What biases occur in peoples' decision making depends on the decision situation, what choices are offered in the choice menu, and what goals the users intend to reach. The second step aims for understanding the users of the information system, which provides essential insights on how to design a digital nudge in the third step.

Step 3: Design the nudge (select and implement) After defining the goals of the intervention and establishing an understanding of the decision situation, choice architects can select from different possible digital nudges. Besides the array of digital nudges described above, nudging frameworks like Behavior Change Technique Taxonomy (Michie et al., 2013), NUDGE (Thaler and Sunstein, 2009), MINDSPACE (Dolan et al., 2012), and Tools of a Choice Architecture (Johnson et al., 2012) provide a set of possible interventions to nudge users towards the desired behaviour, as described in Section 7.2. In contrast to interventions in the physical world, digital nudges are often easy and fast to implement by making adaptions in the front-end of the user interface. Acting in digital environments makes it affordable to test and evaluate the effectiveness of digital nudges in the final step.

Step 4: Test the nudge (measure) The effect of digital nudges depends on both the context and goal of the decision environment and the users. As it is difficult to foresee all factors and implications during the first three steps, it is crucial to test the effects of the intervention on the desired behaviour in realistic situations. Nudges can be tested in online experiments and the field by providing different treatments (i. e., digital nudges) to different users by using A/B testing and split testing based on experimental economics (Friedman et al., 1994). If the nudge does not provide the desired effect, choice architects can move back to previous steps. Then, they can utilise the insights from testing to redesign the nudge (Step 3), use the test results to develop a clearer picture of the users and decision situation, or even adapt the goals of the intervention. A guideline for conducting and analysing such empirical experiments based the social science research is provided in Döring and Bortz (2016). The nudge development and testing in Part III builds on the methods given by Döring and Bortz (2016) and the nudge development process in Mirsch et al. (2017).

The previous chapters in this part show that flexibility from BEVs is valuable for the energy system moving towards more sustainability. However, BEVs users decision on how to charge their BEVs is a bottleneck to the flexibility potential from BEV charging. As financial incentives to charge flexible are low, and BEV users might be frightened to use flexible charging, other measures besides financial incentives might be required to unlock BEVs' flexibility potential (Schmalfuß et al., 2017). Digital nudging provides a powerful tool to establish smart charging without limiting BEV users' freedom or adding costly financial incentives schemes.

Part III.

Behaviour Change towards Smart Charging

CHAPTER 8

BEV USERS‘ OBJECTIVES

This chapter is based on joint work conducted by Julian Huber, Elisabeth Schaule, Dominik Jung, and Christof Weinhardt, published in *World Electric Vehicle Journal*, cited here as: Huber et al. (2019b).

Changing behaviour towards smart charging using digital nudges requires an understanding of the BEV users decision process. An integral part of this decision process is the objective BEV users have in mind when deciding how to charge their BEV. Chapter 5 shows that the objectives prevalent in smart changing systems (i. e., congestion management, ancillary services, etc.) are not naturally in the sphere of interest of BEV users. This chapter analyses what other objectives might motivate BEV users to use smart charging systems. To this end, Section 8.1 summarizes related work on factors that might motivate BEV users to act more sustainable. However, considering only the objectives of BEV users might not result in efficient smart charging systems, as they might not be relevant to the operators and designers of the systems (compare Chapter 5) or might not be feasible from a technical perspective. To integrate the requirements of demand (BEV users) and supply-side (charging station operators), the remainder of the chapter answers the following research question:

RQ 1 *Which objectives of smart charging are likely to motivate BEV users and show high technical potential?*

Section 8.2 describes the methodology of an expert survey that we conduct to validate the findings from the first sections. Based on eight incentive factors for smart charging found in the literature review, we derive statements on the benefits of smart charging. We asked 16 domain experts to evaluate these statements on their technical correctness and their persuasiveness for end users. Last, Section 8.3 and 8.4 present and discuss the results. The chapter ends with a conclusion in Section 8.5

8.1. Related Work

The slow rise of papers considering fairness and social aspects in Figure 5.4 in Chapter 5 indicates that the BEV users' perspective on smart charging has not been considered to the same amount and with the same rigour as the technical aspects. As the flexibility used in smart charging depends on the BEV users' decisions, it is essential to convince them to use such systems. While financial reward might not be sufficient to convince BEV users to use smart charging (Will and Schuller, 2016), they usually have limited knowledge about the energy system and the benefits of smart charging (Biresselioglu et al., 2018). It remains an open challenge to identify the objectives that can convince BEV users to utilize smart charging. This section discusses related work to identify how the users' motivation to use smart charging matches the technical objectives described in Chapter 5.

Reviews and Surveys on BEV users and Smart Charging Will and Schuller (2016) provide a review of twelve studies that research acceptance factors of smart charging. Most of the studies consider the financial (i. e., monetary incentives) and socio-environmental (i. e., RES integration) dimension as positive factors that increase acceptance of smart charging. Three out of twelve studies postulate technical aspects (e. g., contribution to grid stability) as a motivating factor.

In the same paper Will and Schuller (2016) present a survey with 237 BEV users and find a positive influence of RES integration and grid stability on the acceptance of smart charging systems. Interestingly, survey results do not show a positive influence of monetary incentives.

In contrast, in an interview survey with BEV users that used smart charging systems in a field trial, Schmalfuss et al. (2015) find that financial benefits are an essential motivational driver for the usage of such systems. The participants further name RES integration, contribution to grid stability, awareness of energy consumption, and satisfaction from gamification. To gain more recent insights, we perform a forward search for papers citing these two sources (Schmalfuss et al., 2015; Will and Schuller, 2016) and provide the results in the following.

A review provided by Franke et al. (2018) analyses the BEVs users' interaction with BEVs and their charging behaviour in particular. They find that BEV users have individual time-stable differences in the way the drivers charge their cars. They further analyse that interaction with smart charging systems is costly for the user (with reduced mobility flexibility and increased planning effort) and suggest a user-centric design of smart charging systems. The authors stress two points of a user-centric design: Smart charging systems must provide user guidance and assistance in minimizing effort for the user and need to consider the users' objectives in the charging session. These requirements can be addressed by data-driven information systems that could recommend charging settings (see Chapter 6) or provide feedback on avoided CO_2 emissions (see Chapter 10).

Sovacool et al. (2017) provide a review that presents a socio-technical approach for vehicle-to-grid charging. The authors distinguish three types of user intervention in smart charging. Time-of-use pricing, where the users receive price signals and actively decides when to charge their BEV. Revenue sharing, whereby users enter their flexibility for the charging session and receive financial compensation in return. Last, a voluntary shift in charging based on education and non-financial motives. The authors describe BEV users' perception of all the above factors as the behavioural dimension of smart charging and conclude that environmental benefits alone will not succeed in convincing BEV users to use smart charging.

One of the few surveys on the end users' perspective is a discreet-choice experiment by Geske and Schumann (2018) among 611 (conventional) vehicle users, including 14 BEV users. The acceptance of uncontrolled and smart charging is higher than for vehicle-to-grid concepts. Financial and socio-environmental aspects are the main motivating factors for drivers to use smart charging. As drivers lack understanding and interest in the technical details of the electricity system (Biresselioglu et al., 2018) they are little motivated by technical aspects (e. g., avoidance of grid congestion and reserve power plants).

Moreover, the Geske and Schumann (2018) find systematic differences in acceptance for smart charging schemes between drivers with different mobility characteristics, e. g., drivers with high mileage show lower levels of acceptance for smart charging than other drivers. UCSCS should consider such differences and adapt to the particular user and their mobility behaviour. One solution could be personalized charging settings based in individual charging behaviour (see Chapter 6).

Tamis et al. (2017) describe insights from eleven smart charging projects focusing on smart charging in households in the Netherlands. The objectives of these projects are mainly financial and socio-environmental. Five out of them focus on two objectives at the same time (e. g., lowering energy cost while using more local RES). Two of the projects explicitly focus on the community aspect in the socio-environmental dimension, and almost all of the projects try to benefit more than one stakeholder (e. g., end-user, DSO, municipality, or aggregator) at the same time.

Considering the objectives of BEV fleet operators Ensslen et al. (2018) propose a new tariff design for smart charging based on a survey with fleet operators and BEV users. Both BEV users and fleet operators focus on the importance of mobility needs for BEV users, preferring a minimum SoC of 100 km for emergencies. In an earlier study (Ensslen et al., 2016), the same authors focus on fleet owners' willingness to pay for smart charging services. Both the guarantee of a minimum SoC and the use of higher shares of RES to minimize CO_2 emissions have a positive effect on their willingness to pay for smart charging services.

Based on the literature, the design of smart charging systems should focus on fulfilling mobility needs with high convenience and security (e. g., by ensuring a minimum SoC). Besides, financial discounts and the integration of RES are the primary motivators for BEV users to use such systems.

Fit between Operator and User Objectives The literature indicates that financial benefits and integration of RES are the main drivers of acceptance of smart charging systems. However, focusing solely on these two objectives omits an evaluation of the motivational power of other smart charging objectives (e. g., battery degradation, social aspects, congestion management, and ancillary services).

Next, we connect the operators' objectives from Chapter 5 to the perspective of the BEV users to find whether they could also increase acceptance of smart charging if communicated understandably and attractively. Table 8.1 maps the identified objective functions from Chapter 5 with arguments that could convince users to use smart charging systems from the literature.

The arguments are based on the results of the studies collected in the previous section, the literature discusses in Chapter 5 (mainly the search string *'vehicle* $\wedge$ *charging* $\wedge$ *incentives'*), and from related research on nudging towards environmental protection (to be discussed in Chapter 7). We discuss the objectives in the order of Table 8.1.

Table 8.1.: Mapping of smart charging objectives with possible incentives.

Objective	**Incentive**	**Source**
Battery degradation	Battery degradation	Schoch (2016), Schmalfuss et al. (2015)
Cost advantage	Cost advantage	Schmalfuss et al. (2015), Ensslen et al. (2018)
Social aspects	Social aspects	De Groot et al. (2013)
Integration of RES	Integration of RES	Will and Schuller (2016)
	Environmental protection	De Groot et al. (2013)
	Health impact	Asensio and Delmas (2016)
	Climate impact	Barr et al. (2011), Huber and Weinhardt (2018)
Congestion management and ancillary services	Grid impact	Will and Schuller (2016)

Battery degradation is a big concern to many BEV users (Schmalfuss et al., 2015). Using smart charging to slow down battery degradation, as proposed in Schoch (2016), could incentivize drivers to use smart charging.

A large number of studies (US Energy Department, 2015; Schmalfuss et al., 2015; Ensslen et al., 2018; Huber et al., 2019a) find that cost benefits motivate users to use smart charging. To align the operators' financial interests with those of the BEV users, Sovacool et al. (2017) propose revenue sharing concepts to make the user more flexible in charging. This means that users offer their flexibility in their charging settings and are compensated in return, e. g., (Salah and Flath, 2016).

So far, most papers omit aspects of fairness and community building in the design of smart charging systems. Research on energy consumption in households has shown that normative information and feedback on neighbours' electricity consumption can reduce electricity consumption by households (Asensio and Delmas, 2016). Similarly, aspects and the idea of sharing the power grid within a community could also provide an incentive to charge more flexibly (Huber et al., 2018d).

The integration of a higher percentage of RES is an essential driver for users to accept smart charging. Integration more RES has several positive aspects and can be framed towards the user from different angles. First, transparent information about the share of RES in the energy supply mix can motivate and influence users. Following this notion, Germany specifies electricity suppliers to print its generation mix on the customers' electricity bill. Second, the displacement of conventional power plants minimizes emissions of air pollutants. Studies on energy savings show that households consume less energy if they receive information that this behaviour minimizes air pollutant emissions, thereby preventing respiratory diseases (Asensio and Delmas, 2016). Third, besides air pollutants, carbon dioxide emissions can be avoided by load shifting, which could motivate users to use less energy or be more flexible in consumption, i. e., accepting a longer deadline for the charging session.

While the integration of RES has many advantages that are easily understood by BEV users, it seems much harder to communicate the benefits of congestion management and grid operation. Will and Schuller (2016) group concerns about congestion and grid stability and find a positive influence on the acceptance of smart charging. Likewise, we assume that the end-users do not differentiate between voltage quality, frequency, thermal overload, and other grid stability problems (Verbong et al., 2013). Subsequently, we summarize congestion management and provision of auxiliary services with the term grid impact.

In summary, the objectives of smart charging studied in the literature overlap well with the incentives that could convince BEV users to use smart charging systems. We illustrate this in Table 8.1, which presents the mapping of promising incentives for the use of smart charging system and smart charging objectives. In the next section, we conduct an expert survey to analyse which objectives that might work as incentives can also work from a technical perspective.

8.2. Methodology

The literature review in Chapter 5 shows that for charging system operators, energy costs, integration of RES, and auxiliary services are the main objectives of smart charging. At the same time, there are only a few studies that research which factors will convince BEV users to use smart charging systems. Although the incentive factors for the BEV users seem to agree with the objective functions of the operators, there is no clear picture of what the most convincing motivational factors are. Studies even contradict each other, for example, Schmalfuss et al. (2015) find a positive effect of financial incentives while Will and Schuller (2016) do not. As it is unclear whether all motivational factors for using smart charging will work from a technical perspective, we survey domain experts to examine their assessment of the potentials of incentive factors.

Research Design

To identify the most promising incentive factors and objectives, we first grouped the different arguments for smart charging into eight groups based on the results of the literature review (see Table 8.1). For each group, we derive three to five one-sentence statements proclaiming the benefits of smart charging. After a revision round discussing the statements in a round of three scientists convened with information systems and electric mobility, we resulted in 31 statements (see an excerpt in Table 8.2).

We then design an online survey for the evaluation of each statement. In the survey, the domain experts rate each statement regarding its technical accuracy and expected persuasiveness towards end-users. Getting the agreement of the experts to assess statements is a standardized procedure, which is also used in the Delphi method to reach consensus between expert opinions (Linstone et al., 1975).

We distributed the survey within a German state-funded research project[1] and other channels to professionals in the domain of electric mobility. The survey was online from 30.07.2018 to 6.8.2018. The 16 completed surveys included researchers in electric mobility (10), car manufacturers (1), grid operators (3), and consultants for electric mobility providers and the energy sector (2). As an incentive for each completed survey, we donated 5 € to a non-governmental organization[2].

In the following, we report the English translations of the responses. The evaluation of the statements are rated on a five-level Likert scale from disagreement *strongly disagree' (stimmt nicht)* to *'strongly agree' (stimmt völlig)* to this statement being technically correct or persuasive (compare Döring and Bortz (2016)). We operationalize perceived technical accuracy by agreement on *'In my opinion, this statement is technically correct.' (Diese Aussage scheint mir fachlich korrekt)*. The perceived persuasiveness towards end-users by agreement on *'In my opinion,*

[1] www.csells.net/

[2] www.akcjamiasto.org concerned with sustainable mobility in Wrocław, Poland

this statement can convince users' (Diese Aussage scheint mir Nutzer überzeugen zu können).

Example statements for the distinct incentive factors are provided in Table 8.2. The full set of statements is noted in the appendix Table C. At the end of the survey, participants rated their ability to evaluate the statements correctly and stated their domain background.

Table 8.2.: Translation of examples for incentive statements used in the survey.

Incentive	**Example Statement**
Battery degradation	*Flexible charging can help protect the battery.*
Cost advantage	*Flexible charging allows the user to benefit from lower electricity prices.*
Social aspects	*The power grid is shared with other users and benefits from the fact that they are flexible when charging BEVs.*
Integration of RES	*If users provide charging flexibility, the BEV can be charged with more solar and wind power.*
Environmental protection	*Flexible charging allows more electricity from RES to be used, thus protecting the environment.*
Health impact	*Charging flexibility can avoid conventional generation and thus save harmful emissions.*
Climate impact	*Additional temporal flexibility can make a positive contribution towards mitigating climate change.*
Grid impact	*Flexible charging contributes positively to grid stability.*

8.3. Results

Table 8.3 lists the incentive factors based on the highest ranking in the two categories. It becomes evident that the two categories are ranked similarly, i. e., what is viewed as correct is also viewed as persuasive, with only minor differences. The incentive factors *integration of RES*, *cost advantage*, and *environmental protection* rate with the highest persuasiveness (i. e., from 4.4 to 3.9 out of the maximum of five points). These groups, along with *grid impact* are also the top-rated in their accuracy (from 4.4 to 4.2).

Table 8.3.: Ranking of groups based on accuracy and persuasiveness rating.

Group Ranking	**Mean Accuracy**	**Group Ranking**	**Mean Persuasiveness**
Grid impact	4.4	Cost advantage	4.4
Integration of RES	4.4	Integration of RES	4.1
Cost advantage	4.3	Environmental protection	3.9
Environmental protection	4.2	Climate impact	3.6
Climate impact	3.8	Grid impact	3.5
Health impact	3.6	Social aspects	3.3
Social aspects	3.4	Health impact	3.1
Battery conservation	2.9	Battery conservation	2.9

The domain experts were very confident in their evaluation: 13 out of 16 agreed or agreed strongly to the statement that they could correctly assess the technical accuracy of the statements, only three out of 16 said they partly agreed.

8.4. Discussion

Figure 8.1 shows a scatter plot of all statements in the two dimensions (persuasiveness and technical accuracy). The plot shows that the statements belonging to one incentive always cluster tightly. The closeness indicates that the pre-selection generated similar statements that belong to the same incentive.

However, there is one exception evident in Figure 8.1: One statement regarding the social aspects of smart charging rates much higher than the other two. The statement rated higher reads: *'The power grid is shared with other users and benefits from the fact that they are flexible when charging BEVs.'*. It combines social aspects (i. e., use of a common good) with a positive impact on the grid. On the contrary, the other statements in this group are normative messages without any mentioning of other objectives (*'BEV users agree that charging should be flexible.'* and *'Others of the charging station usually allow smart charging.'*). While the experts rate these normative statements low in persuasiveness, studies by Schultz et al. (2007) show that normative framings can persuade users to behave more environmentally friendly.

In summary, the results show that experts consider those smart charging schemes as most persuasive, which they consider technically correct. Moreover, cost savings and integration of RES are rated highest on both scales. This result corresponds to the high number of papers with these objectives found in the literature. The

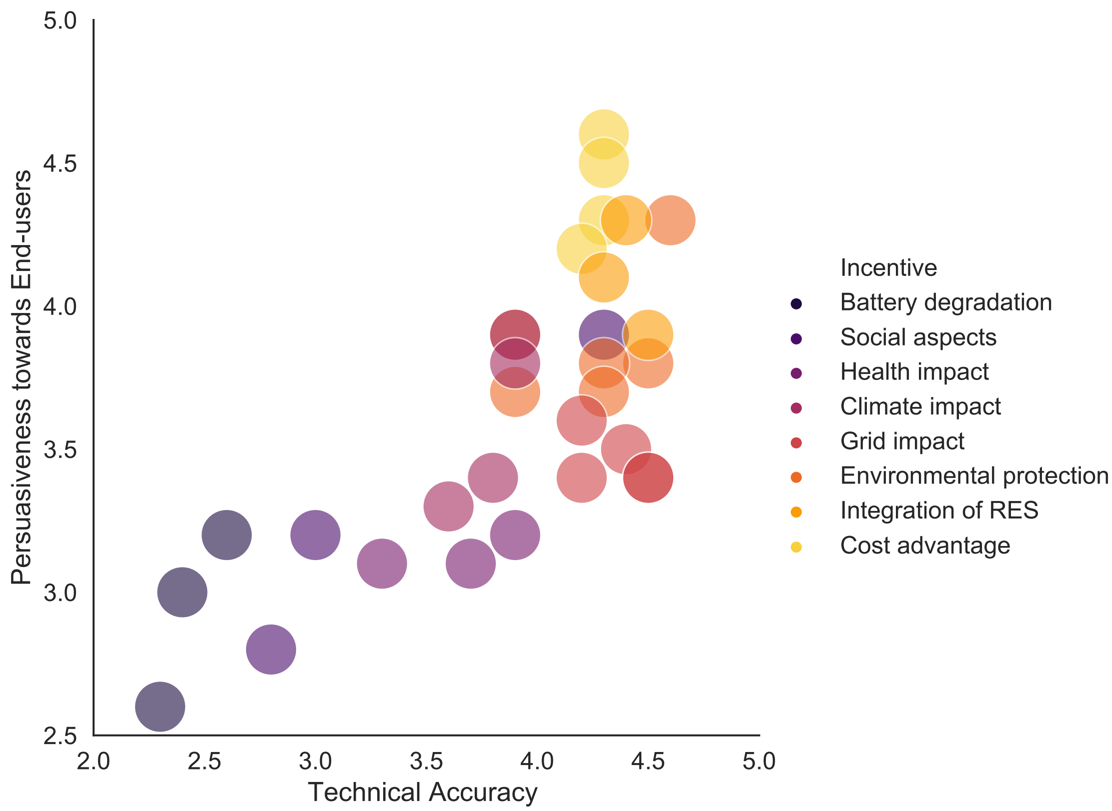

Figure 8.1.: Statements on benefits of smart charging evaluated on their technical accuracy (x-axis) and persuasiveness towards end-users (y-axis).

integration of RES has indirect benefits (e. g., on climate, health, and air pollution) that score lower than statements regarding the integration of RES itself.

A positive impact of smart charging on battery degradation is rated as rather low and not very convincing. In one expert's opinion, the OEMs already optimized charging to ensure long battery life and no further improvements could be achieved by smart charging.

As the sample of experts is rather small and biased towards research, this might explain why the experts' opinion is in line with the objectives found in the literature. However, the industry experts do no deviate in their responses. As there was a little deviation in the experts' opinions, a method for generating consensus (e. g., Delphi Method) is not needed.

8.5. Conclusion

In this chapter, we identify the objectives for charging station operators and incentives for BEV users to use smart charging systems. Different charging system operators intend to use the flexibility potential from smart charging (Chapter 5) for different objectives. Out of these objectives, literature names the cost advantage and integration of RES as the most significant incentives for BEV users to use smart charging systems. This ranking fits the domain experts' assessment that smart charging can contribute primarily to cost reduction and the integration of RES. At the same time, the experts assess cost reduction and the integration of RES as most convincing towards end-users. However, this assessment contradicts the findings of Will and Schuller (2016), where BEV users stated that financial incentives were not relevant for early adopters of BEVs. Although the avoidance of grid congestion is a relevant area of application, experts doubt that this objective can convince users to use smart charging.

As cost reduction and integration of RES are shared objectives of BEV users and charging system operators, these objectives could directly incentivize BEV users to use smart charging. However, there are different ways to communicate the benefits of the objectives towards the BEV user. For instance, the integration of RES can be framed as having health or climate benefits (see Chapter 5). Experiments and surveys with BEV users could help to understand which framing is the best to inform and convince the BEV users to act more sustainably (Staudt et al., 2019). Finally, the design of the UCSCS should not only consider the operator's optimization objectives but also how these targets are communicated to the BEV users. In the next chapter, we analyse how framing smart charging towards different objectives influences the behaviour of the BEV users.

CHAPTER 9

GOAL FRAMING IN SMART CHARGING

This chapter is based on joint work conducted by Julian Huber, Elisabeth Schaule, Dominik Jung, and Christof Weinhardt, published in *Proceedings of the 27th European Conference on Information Systems (ECIS)*, cited here as: Huber et al. (2019a).

The previous chapter shows that smart charging has many promising fields of application. While smart charging systems may look promising, academic literature does not yet show evidence of their economic success in the field (Hossain et al., 2016). A reason for this might be, that smart charging has to be tackled on multiple levels: while most of the recent studies focus on technical solutions or economic incentives from a provider-perspective, Schmalfuss et al. (2015) note that little attention has been paid to the charging session from the users' perspective. This chapter expands on the expert-survey of the previous chapter and evaluates the identified objectives on BEV users. As the provision of charging flexibility may conflict with the mobility needs of the user, smart charging systems usually require the users to type in their charging preferences into the user interface explicitly, e. g., entering planned departure time and desired SoC. Thereby, the BEV users might not offer enough flexibility to fulfil the objectives they aim for with smart charging.

vom Brocke et al. (2013) and Watson et al. (2010) raise the question of how information systems can be designed to reduce the effects of climate change and other environmental problems. One solution might be that information systems facilitate sustainable actions in end-users. In particular, Melville (2010) presents a believe-action-outcome framework that describes how sustainable actions in information system users emerge from their beliefs, desires, and opportunities. The author fills the framework with ten research questions for a research agenda to increase sustainability with information systems. For instance, to strengthen the path between belief and action the author asks information system researchers to tackle the research question: *'What design approaches are effective for developing information systems that influence human actions about the natural environment?'*.

As mentioned in Chapter 7, digital nudging is very recent pathway in information systems research to strengthen this path and to align these provider- and user-specific objectives for a better outcome. Choice architecture and nudging is a behavioural economics tool to push people towards optimal decision-making without restrictions or economic incentives (Thaler and Sunstein, 2009). Recent work identified this approach as a promising pathway to support decision-making in information systems like e. g., to reduce range anxiety (Huber et al., 2018e; Franke et al., 2012; Eisel et al., 2016; Huber et al., 2018d), increase acceptance of BEVs (Stryja et al., 2017b,a), or to overcome inertia or biased decision-making (Jung and Weinhardt, 2018; Stryja et al., 2017a).

In this chapter, we adept the research question from Melville (2010) to the context of smart charging and evaluate whether digital nudging is a promising approach to increase sustainable behaviour. We provide a cross-context theory replication digital nudging into the domain of smart charging systems (Hong et al., 2013). In particular, we analyse to what degree the motivational factors from the previous chapter can be applied to increase charging flexibility of BEV users:

RQ 2 *To what extent can framing messages in user interfaces influence the flexibility in BEV users' charging settings?*

The remainder of the chapter is structured as follows. We start by describing the related work in Section 9.1. Building on this, we derive our hypotheses in Section 9.2. Section 9.3 describes the research design for hypothesis testing, the nudge development process, the procedure and operational of the online experiment, and the statistical analysis of the results in Section 9.4. The chapter concludes with a discussion of the results in Section 9.5 and 9.6.

9.1. Related Work

This chapter starts with giving a brief behavioural-economic background on choice architecture and nudging and how this concept influences information systems research. Next, we discuss the results of a structured literature review (Webster and Watson, 2002) on the effects of (digital) nudging on sustainable behaviour in the energy context. The literature review is based on a forward-backwards search starting from papers on dual-processing theory, nudging and choice architecture, digital nudging, energy conservation, smart charging, and integration of RES. Afterwards, we discuss the most important results of the literature review on the motivational factors for using smart charging of BEVs.

Recent findings from behavioural economics and psychology suggest that humans often use simplified decision-rules and heuristics instead of deliberative thinking in everyday decision-making (Thaler and Sunstein, 2009). Following this rationale, the dual-processing theory suggests that human judgment and decision-making is driven by two distinct types of cognitive processes: Automatic-intuitive processes and controlled-deliberate processes (Evans, 2008). The latter requires more time and conscious effort to complete. Automatic processes, on the other hand, are fast, intuitive, and based on reflexes. They make up a large number of our decisions and come into play in everyday situations or are used as a rule of thumb or heuristically to support a fast decision process (Mirsch et al., 2017). As a consequence, the need to consider both human styles of decision-making in system design have been raised (Mirsch et al., 2017; Thaler and Sunstein, 2009). Thaler and Sunstein (2009) propose to design and organize the decision environment methodically to improve human decision making. This approach is also called choice architecture or nudging and can be applied in a digital decision environment as digital nudging (Weinmann et al., 2016). Chapter 7 provides background knowledge on choice architecture and the development of digital nudges.

Framing A common nudge introduced in Chapter 7 is framing. Framing is the conscious formulation and description of the decision situation to encourage people to behave in a certain way. Thaler and Sunstein (2009) argue that framing can be a successful nudge, as the preferences of humans can change with the question that is raised in the decision situation (Tversky and Kahneman, 1981). In particular, goal framing focuses on the goals that can be reached or outcomes that can be avoided depending on the decision at hand.

On a psychological level Lindenberg and Steg (2007) explain the effectiveness of goal framing towards environmental-friendly behaviour by three overarching goals acting as primary motivators in human behaviour. Hedonistic goals are the pleasure or absence of adverse experiences felt directly during the activity without considering the overarching goals. Hedonistic goals can explain a good part of non-sustainable behaviour. For instance, taking a car is more convenient than waiting for a cramped bus. Normative goals are set by other peoples behaviour and social values. Schultz et al. (2007) leverage the urge to apply to normative goals as a nudge. The authors provide households with feedback on their energy consumption compared to their peers. In the field experiment, the participants followed this normative framing and adapted their energy consumption towards the norm (i. e., lavish households reduced, and fugal households increased their consumption). Last, gain goals are the desired outcomes of the action. Goal framing can shift the relative weight between these goals towards normative or gain goals, e. g., by highlighting the benefits of objectives, to induce environmental-friendly behaviour. In this way, framing influences the belief formation described by the belief-action-outcome framework (Melville, 2010).

According to Mirsch et al. (2017) framing is the digital nudge that is most frequently studied in information systems research. In particular, framing has been successfully applied to encourage environmental-friendly behaviour. As an example of the use of choice architecture, Asensio and Delmas (2016) use framing to promote energy conservation in households. They test negative framings on health-focused goals (health damages associated with emissions) and positive cost-savings (emphasizing the monetary benefits of saving energy) included in a physical feedback letter on the households' energy consumption. The authors find the health-based framing led to 8-10 % more energy conservation over a period of one hundred days. A framing on cost savings, however, had only a short-term effect. After two weeks, energy savings increased by a significant amount after fifty days, there was no difference in energy savings compared to the neutral control group. The finding that monetary framings are not effective long-term is supported by a meta-analysis where different framings and informational messages on household energy consumption were investigated by Delmas et al. (2013). The authors conclude that monetary framings are not effective over a extended periods.

Another example of successful framing is the adoption of biofuel. Moon et al. (2016) find that negatively framed messages, i. e., focusing on negative impacts of gasoline compared to the benefits of biofuel, were more effective in enhancing social desirability of biofuel adoption. This result shows that the direction of the framing can have a substantial influence on the effectiveness of framing. Another important finding of the authors is that framing does not work the same way for all participants. Attributes found to be associated with biofuel adoption were the level of environmental concern, pro-social behaviour, and openness to new experiences of the participants.

These findings are in line with other studies, that find that goal framing focused on losses are more effective in a decision situation, where one option is considered harmful or risky. In contrast, framings focusing on gains (i. e., positive goal framings) seem to be more effective for behaviour that is considered non-risky or is for prevention reasons, e. g., breast examinations for early cancer identification (Meyerowitz and Chaiken, 1987).

Another moderating effect on the success of message framing towards sustainable consumption is the environmental concern of the decision-maker. Newman et al. (2012) find that consumers with low and high concern react similarly towards negative framing messages. However, a positive framing increases the likelihood of sustainable behaviour in the high-concern group while it lowers the likelihood in the low concern group.

De Dominicis et al. (2017) investigate how another character trait influences how well framing works for different individuals. The authors analyse the impact self-interest and altruism had on incentivizing pro-environmental behaviour. The results show that different types of framing the intended pro-environmental behaviour work for increasing pro-environmental for altruists and self-interested individuals.

These results show that nudging, especially framing, can be successfully used to encourage environmentally-friendly behaviour. However, it cannot be generalized which arguments, e. g., health, environmental protection, and which direction of framing, e. g., negative or positive, is most promising in the context of BEV charging as it also depends on the individual decision-maker.

Decision Frames of BEV Users To account for the differences in decision situations, the digital nudge development process by Weinmann et al. (2016) illustrates the need for an understanding of the individual decision situation before promising nudges can be identified (see Chapter 7). Hence, the following literature presents insights into the motivation of BEV users to use smart charging systems. An in-depth discussion on the BEV users' objectives when using smart charging systems is provided in Chapter 8.

Due to its limited range of BEV compared to conventional cars, many BEV users suffer from range anxiety (Franke et al., 2012). The primary goal of users who connect their BEV to a charging station might be to fill the battery with enough energy to meet their mobility needs. This idea is emphasized by the findings of Will and Schuller (2016), who surveyed early BEV adopters on the acceptance factors for smart charging. Only four out of 13 factors show a significant influence on the acceptance of smart charging systems. The impairment of flexible mobility needs was the only significant adverse effect.

Motivation factors with a positive effect are a contribution to grid stability, followed by integration of RES. Monetary incentives in the form of discounts to the electricity price per kWh or discounts on the electricity base price were not significant. These results are supported by the qualitative interviews conducted by Schmalfuss et al. (2015). Subjects named a contribution to network stability, financial benefits, environmental benefits by the integration of RES, awareness of energy consumption, satisfaction from gamification, and financial benefits for energy suppliers as positive factors. On the downside, they stated losses in the flexibility in mobility needs and comfort and data privacy concerns.

The fact that Will and Schuller (2016) find no effect for monetary incentives is an essential insight as many papers and field studies implement financial incentives to encourage smart charging behaviour. For instance, Jian et al. (2018) conduct a case study and show that charging tariffs with significant price gaps between on- and off-peak prices are an essential incentive to encourage smart charging. The US Energy Department (2015) conducted a case study with different prices charging during on-peak, off-peak, and super off-peak hours. These price signals had an impact on BEV users' charging behaviour. Note that the last case study does not use smart charging systems; in contrast, BEV users must actively plug-in their BEV during the right time slots. Jochem et al. (2012) used monetary incentives (i. e., dynamic tariffs) successfully to shift users' charging to off-peak hours. The authors also report that if the optimized charging session were automated and ensured a higher integration of RES, the users would show more acceptance for this process. Following these findings, a combination of financial and non-financial incentives, e. g., nudging, could be the key to implementing high acceptance of smart charging schemes.

9.2. Hypothesis Development

To the best of our knowledge, the influence of digital nudges on the use of smart charging systems has not been studied so far. The impact of different nudges on energy conservation, however, has been successfully demonstrated repeatedly. In particular, framing has been used in many areas of environmental sustainability to encourage environmental-friendly behaviour. In some cases, framing was even more successful than monetary incentives (Asensio and Delmas, 2016; Delmas et al., 2013).

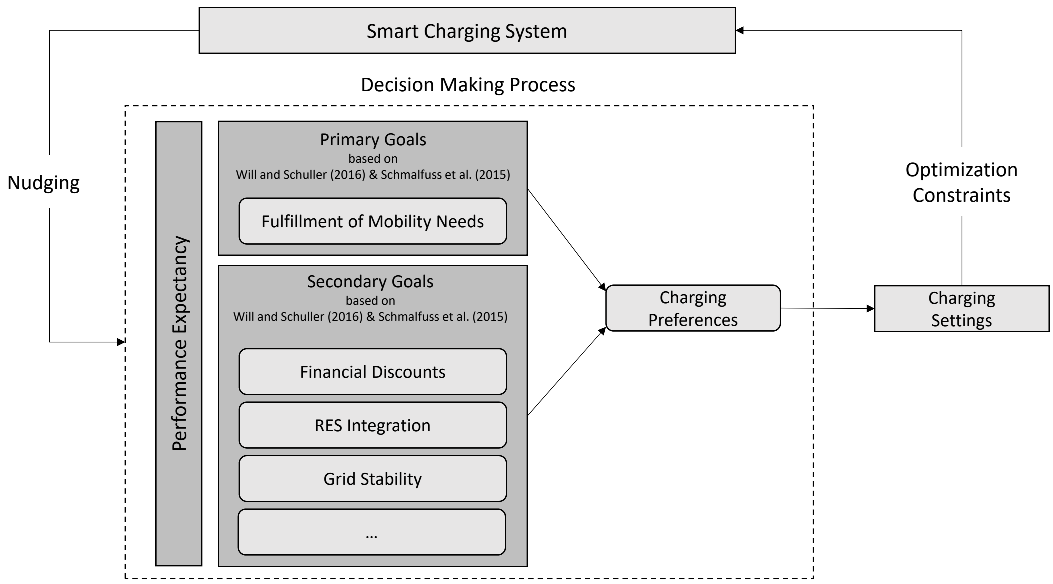

Figure 9.1.: Theoretical context and research framework of this study, adopted from Jung and Weinhardt (2018) and Loock et al. (2013a)

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Following the diagnose step of Weinmann et al. (2016), we hypothesize that the users' acceptance of smart charging system depends on the objectives of the smart charging systems. Making these objectives more salient, i. e., by framing messages in the user interface, should influence the BEV users' belief formation and nudge them towards higher flexibility in their charging settings (Tversky and Kahneman, 1981; Lindenberg and Steg, 2007).

Other digital nudges, such as default or feedback, might as well increase charging flexibility. However, there is not much insight into the real-world charging behaviour of BEV users yet. In contrast, the literature outlined in Chapter 8 provides a good understanding of the objectives BEV users fancy in smart charging systems. In this first study on the effect of digital nudges on the use of smart charging systems, we look into goal framing as a promising digital nudge to increase charging flexibility of BEV users.

Based on the conclusions discussed in this section, Figure 9.1 shows the theoretical context for this study. A smart charging system is an information system that controls the charging session within the optimization constraints given by the user. It can target various optimization objectives, such as cost and CO_2 emission minimization, or the avoidance of grid congestion. The higher the flexibility in the users charging settings, the better the optimization objectives can be met. Usually, multiple of these objectives can be achieved simultaneously, e. g., when shifting charging towards cheap and emission-free RES generation (Huber and Weinhardt, 2018). In this way, the decision situation remains identical, but it can be framed in different ways (i. e., towards different objectives). At the same time, the interface of the smart charging system provides the decision environment for the BEV user and can thus influence the users' decision process.

Within the decision process and belief formation, the preferences on how to use smart charging are driven by the expected performance of the smart charging system. Primarily, users expect that the smart charging system will charge their vehicles in a way that meets their mobility needs (Will and Schuller, 2016; Schmalfuss et al., 2015). BEV users might even consider smart charging as a risky situation if they suffer from range anxiety (Huber et al., 2018e), which would be an argument to provide no charging flexibility.

Secondarily, that further goals, such as financial savings, integration of RES, and grid stability can influence the acceptance and motivation to use smart charging. Goal framing points the focus on specific goals during the user's decision-making process and should increase the motivation to use smart charging. This charging preferences (i. e., beliefs) determine what the user enters as her charging settings (i. e., actions) into the system. In this way, digital nudging could influence believe formation and lead to more sustainable actions (e. g., higher time flexibility in the charging settings).

Other factors influencing the charging behaviour, such as effort expectancy, social influence, or facilitating conditions as described by Venkatesh et al. (2003) are not considered in this study. Based on these considerations, we hypothesize that the insertion of framing messages towards secondary objectives in smart charging systems increases flexibility in BEV users' charging settings.

9.3. Methodology

To test the effect of the framing messages on the flexibility of the BEV users, we design a scenario-based choice online experiment (comparable to Momsen and Stoerk (2014); Codagnone et al. (2016); Székely et al. (2016)). Momsen and Stoerk (2014) emulate the electricity tariff selection on a website to test the effectiveness of different digital nudges, while Codagnone et al. (2016) research the effect of eco-friendly framing on the choice of conventional vehicles. Such experiments cannot provide full external validity. However, they are useful to tool for understanding the potential of nudging and offer more in-depth insights into the decision process.

Similar to the tariff selection in Momsen and Stoerk (2014), our experiment explains the decision situation as an onboarding process at the first setup of the smart charging system in which the participants can set the standard preference for each scenario, which the participants can override for each particular charging event. The idea behind this scenario is that participants are less influenced by their specific daily schedule, as they know they could overrule the decision at any time. In practice, such a precommitment could help BEV users to stay with their good intentions to provide flexibility (compare Becker 1978).

In the following section, we describe the research design and procedure of this experiment. We then explain the nudge development based on the literature review and an expert survey from Chapter 8. In Section 9.3.3, we provide the sample and the scenarios and finally explain the choice of control variables and their operationalization.

9.3.1. Research Design

In the experiment, participants are asked to use a mock-up of a smart charging application to set their default charging settings for three different scenarios (see Figure 9.2). We use a between-subject design to measure the effect of the three selected framing messages compared to a control treatment.

The charging settings are entered via two sliders, with anchors at the SoC at arrival and the maximum SoC expressed in km. With the first slider the participants can set the buffer SoC SoC^b to be reached at the highest possible charging power. Note that this is a common feature in user interfaces for smart charging (Dronia and Gallet, 2016). Second, participants enter the final SoC SoC^d for the planned time of departure t^d (see Figure 5.2). The planned time of departure is given by the scenario. A field over the slider position indicates the selected SoC in km.

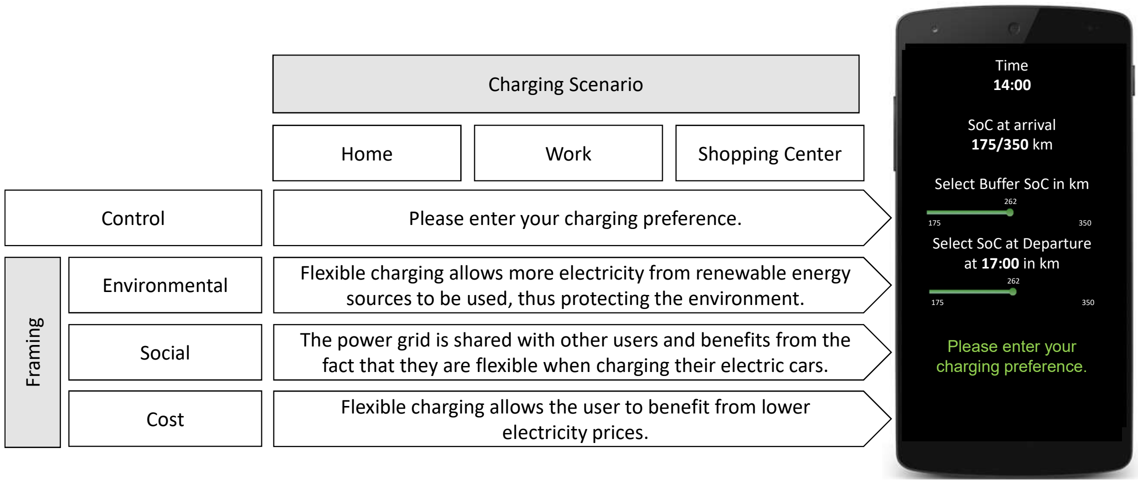


Figure 9.2.: Set-up of charging scenarios and framing messages in the online experiment (translated from German).

The control group enters their charging flexibility in a charging application (Figure 9.2) with a neutral message (The green text stated: *'Please enter your charging preference'*). This is replaced for the three treatment groups by the treatment framing messages, i. e., environmental, social, and cost framings. The experiment is conducted as an online survey where the participants were randomly assigned to either one of the framing treatment groups or a control treatment group. The temporal procedure is structured as follows. First, the introduction and description of basic setup. Second, the scenario-based choice experiment (see Figure 9.2). Third, the questionnaire to capture demographic data and controls.

9.3.2. Nudge Development

Our goal is to design a user interface for a smart charging system that encourages users to be more flexible and thus more sustainable in their charging session. BEV users how use smart charging systems are usually in favour of using smart charging to reach environmental friendly goals (Will and Schuller, 2016; Schmalfuss et al., 2015). Choice architecture and (digital) nudging provide designers a tool to steer users toward more environmental friendly decisions.

Steps	1. Define	2. Diagnose	3. Select	4. Implement	5. Measure
Objective	Definition of Context and Goals	Understanding of Decision Process to Determine Relevant Psychologigcal Effects	Selection of Appropriate Nudges to Alter Behavior	Design of Nudges and Choice Architecture	Evaluation of Nudges
Implementation	Identification of Challenges in Smart Charging (Chapter 4 & 5)	Literature Review on Smart Charging and Nudging towards Sustainability (Chapter 8)	Expert Survey: Nudge Development (Chapter 8)	Online-Experiment: Implementation and Experimental Setup (Chapter 9)	Online-Experiment: Evaluation and Discusson (Chapter 9)

Figure 9.3.: Nudge development process adopted from Mirsch et al. (2017) and Weinmann et al. (2016).

We adopt the five-step nudge development process from Mirsch et al. (2017); Weinmann et al. (2016) described in Chapter 7. The resulting research framework is presented in Figure 9.3. The first two steps include the definition of context and goals and the understanding of the decision process. We outline the challenges in smart charging in Part II of the dissertation and provide insights into the BEV users decision process based on a literature review in Section 8. The considerations from Section 9.2 lead us to framing messages as promising nudges to enhance charging flexibility. Following the framework, in this section, we select possible nudges. For that purpose, we conduct a survey with 16 domain experts evaluating the potential of different framing messages, derived from a systematic literature review.

The procedure and results of the expert survey are discussed in Chapter 8. The arguments to provide charging flexibility found in the literature review are grouped into eighth motivational factors or goals of smart charging. Table 9.1 extends Table 8.1 by presenting goals of charging flexibility identified in the literature review.

The results from the literature analysis and the expert survey form the foundation of the next step in the nudge development process. For that purpose, we select framing messages for the online experiment based on the results. For the treatment message, we choose the strongest framing messages from the three most convincing and most accurate clusters (compare Table 8.3). The selected messages for environmental (4.3, 4.6), social (3.9, 4.3), and cost (4.6, 4.3) framing are shown in Figure 9.1. Consequently, we evaluate the effect of goal (i. e., cost and environmental) and normative (i. e., social) framing on the BEV users' charging flexibility.

9.3.3. Participants and User Scenario

To capture the BEV users' behaviour in various settings, participants have to enter their charging settings for three different scenarios (see Table 9.2 and Figure 9.2). To control for the participants personal risk preference and differences in individual mobility patterns, the scenario was explained as an onboarding process. An onboarding process is the first setup of the smart charging system in which the participants can set the standard preference for each scenario. The participants were informed that they could deviate from this setting during each following charging session.

The scenarios are constructed to mimic typical situations of full-time employees commuting to work and having the opportunity to charge at both locations, at work, and at home (Sadeghianpourhamami et al., 2018). Each scenario has a different SoC at the time of the arrival at the charging station so that it was more or less urgently necessary to charge to have sufficient range for the next planned trip, e. g., work scenario. In the case of the home scenario, the user has enough range to get to work but not to commute back. In this case, the user has to rely on the charging opportunity at work. In the shopping centre scenario, the user has plenty of range to get back home and even to work and back the next day if necessary.

These scenarios are designed deliberately this way to capture more reliable and realistic data on users' overall charging behaviour. The car in the scenario is set

Table 9.1.: Goals and incentives for provision of charging flexibility.

Goals	**Description**	**Source**
Battery Life	Smart charging can prolong battery lifetime because non-flexible charging strains the battery	Schoch (2016)
Cost Advantage	BEV users can benefit from reduced energy costs when using smart charging, for example, when charging during off-peak hours that include lower energy prices. Cost has been shown to be an effective incentive for BEV user to use smart charging	US Energy Department (2015); Will and Schuller (2016); US Energy Department (2015); Jian et al. (2018); Jochem et al. (2012)
Social Aspects	As in energy conservation BEV users might be influenced by their peers' behaviour or may be influenced when their actions can help others or are exposed to a normative standard	De Groot et al. (2013); De Dominicis et al. (2017)
Environmental Protection	Smart charging can be used to help protect the environment by reducing the usage of polluting fossil energy sources	De Groot et al. (2013); Gottwalt et al. (2013)
Integration of RES	The use of flexible charging can allow the integration of more RES such as solar and wind power to charge the BEV	Will and Schuller (2016); Nienhueser and Qiu (2016); Gottwalt et al. (2013)
Grid Stability	With the flexibility of smart charging the grid can be used more efficiently and help avoid grid congestion	Will and Schuller (2016); Clement-Nyns et al. (2010)
Climate Change	Smart charging can support the integration of RES which can minimize CO_2 emission that can impact climate change	Barr et al. (2011); Spence and Pidgeon (2010); Huber and Weinhardt (2018)
Health Impact	Integration of a greater portion of RES minimize pollution from fossil power generation, thus reducing related health risks, e. g., asthma	Asensio and Delmas (2016)

to have a maximum range of 350 km based on the current state of the art Tesla Model 3[1] which is similar to other BEVs in Table A in the appendix.

Table 9.2.: Charging scenario details in the online experiment.

	Home	**Work**	**Shopping center**
Arrival time	6:00 pm	8:30 am	2:00 pm
SoC	30 %	9 %	50 %
Range left	105 km	30 km	175 km
Next time to drive	7:30 am	5:30 pm	5:00 pm
Next trip distance	75 km to work	75 km back home	10 km back home

9.3.4. Operationalization and Control Variables

The smart charging interface offers the user the possibility to enter the range that the charging system should reach as soon as possible at time t^b and the range to be reached at the planned time of departure t^d (see Figure 5.2). The time of departure and the range available when connecting to the charging station SoC^a and the maximum range of the BEV SoC^f were given by the scenario.

As the room for optimization of the charging session depends on both SoC^b and SoC^d, we introduce a metric for charging flexibility based on their difference. The flexibility of the BEV user for a given charging scenario s depends on the SoC^a and SoC^b. Further, to allow a comparison between the three charging scenarios S, we introduce a common metric to evaluate BEV user's u charging flexibility ζ_u by normalizing the flexibility with the maximum of the possible flexibility $SoC^f - SoC^a$. Note that the time of departure is not considered in this metric as it is preset by the scenario description and not selected by the participant. We calculate the charging flexibility as

$$\zeta_u = \sum_S \frac{1}{|S|} \frac{SoC_s^f - SoC_s^b + SoC_s^f - SoC_s^d}{2(SoC_s^f - SoC_s^a)}. \tag{9.1}$$

With this metric, the flexibility can be summarized in a single number between zero and one. Zero indicates no flexibility (i. e., the BEV is fully charged as fast as possible). One is the maximum flexibility (i. e., the BEV does require charging at all but can be used to catch a surplus of power supply of the grid).

[1] www.tesla.com/de_DE/model3

The survey ends with questions on the participants' socio-demographic factors such as age, gender, net monthly income, and occupation. We further ask an open question on the benefits of charging flexibly to capture prior knowledge. As a filter question, we required the ownership of a valid driver's license. To control for the influence of the persons driving pattern, we ask for the weekly frequency of car trips and the average weekly distance travelled in the car. We expect that users with more and longer trips have less leeway to charge flexibly. Last, we capture the prior experience with the technology by asking about possession of a hybrid or electric vehicle, and e-bikes. As the framing messages address the environmental and social behaviour and Kranz and Picot (2011) find that environmental concern drives the adoption of information systems, we also control for the environmental concern. The effect of environmental concern is also stressed by Moon et al. (2016) and Newman et al. (2012) who also found an influence of pro-social behaviour on the effectiveness of framings. We control for the agreeableness of the participants to address such effects. Since the decision to charge flexibly involves the risk of not being able to use the BEV spontaneously because it is not yet sufficiently loaded, the willingness to take risks is also assessed.

Environmental concern and the agreeableness is evaluated on a five-level Likert scale used in (Grunenberg and Kuckartz, 2013; Rammstedt et al., 2013). The willingness to take risks is implemented as one item scale from Dohmen et al. (2011). We further add a ten-item short-version for the big five personality traits to capture the agreeableness of the participants (Gosling et al., 2003). For socio-demographic factors as well as the driving and car usage (i. e., frequency of car use, ownership of a BEV, or an e-bike) the participants are asked to state their information based on grouped clusters, e. g., levels of income or yes/no questions.

9.4. Results

In the following, we describe data collection process and the resulting data set. Subsequently we present the survey results.

To collect a representative sample with actual BEVs users, the study was distributed online in German forums and social media groups focused on electric mobility[2]. As an incentive, full answers could participate in a lottery with Amazon vouchers. Out of 171 completed responses, we removed underage participants (one) and samples with invalid entries (six). The evaluated 164 measures (40 female, average age 38.8, median age 40.0, age group between 18 and 70) corresponds to the expectations at a proportion of 78 BEV owners. Table 9.3 presents a descriptive analysis of the sample. The sample corresponds to the typical German buyers of electric vehicles who are typically around forty years old, male, and well-educated (Frenzel et al., 2015).

Table 9.3.: Descriptive analysis of the sample in the online experiment.

	Unit	**Mean**	**Standard Deviation**
Age	Years	38.8	14.3
Gender	%	75.6	43.1
Willingness to take risk	{1, 10}	5.4	2.1
Number of weekly Trips	1	4.7	1.8
Weekly trip distance	km	114.0	178.2
Environmentalism	{1, 5}	3.9	0.6
BEV ownership	%	47.6	50.0
Flexibility	%	59.2	19.0

The mean charging flexibility metric over all charging scenarios presented in Figure 9.4 is 0.586 (Standard Deviation (SD) $= 0.185$) in the control treatment. The subjects in the cost treatment ($0.673, \mathrm{SD} = 0.182$) and the environmental treatment ($0.597, \mathrm{SD} = 0.197$) entered a higher flexibility. The subjects exposed to the social framing message show a lower flexibility ($0.495, \mathrm{SD} = 0.158$). This pattern is consistent throughout all charging scenarios. The flexibility in the cost treatment is the highest, while the social framing message results in the lowest charging flexibility.

To answer the research question to what extent different framing messages can influence the charging flexibility of BEV users, we compare the flexibility entered for the three treatments with the flexibility entered by the control group. As we are interested in the effect of different treatment groups, an ordinary least square regression in Table 9.4 regresses the different treatments (coded as dummy variables) on

[2] elektroauto-forum.de, tff-forum.de, goingelectric.de; Facebook groups: TESLA Enthusiasten D-A-CH, Elektroauto D-A-CH-FL

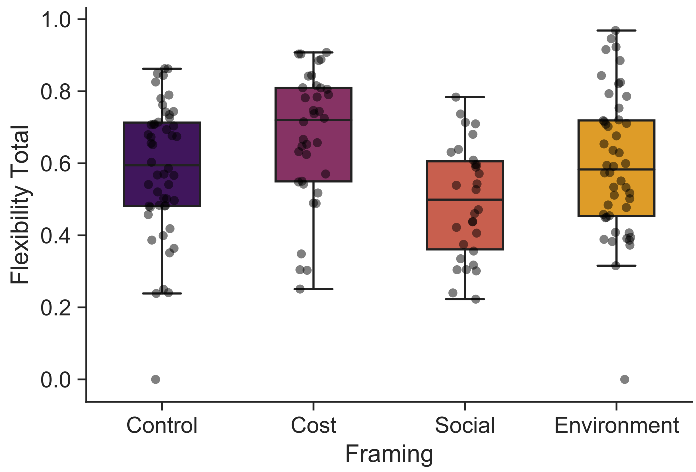


Figure 9.4.: Box plots of flexibility over all charging scenarios grouped by treatment groups.

the mean charging flexibility over all charging scenarios. After testing the regression assumptions, this allows a comparison of effect sizes to other studies in the field, e. g., Jung and Weinhardt (2018). Compared to the control treatment, the charging flexibility in the group with the cost framing shows a significant increase of 8.73 percentage points. In the group with the social framing message, the flexibility is 9.04 percentage points lower compared to the control group. Although the differences between the mean values of the control group and the environmental framing are not significant, Figure 9.4 shows that some participants in the environmental group provide the highest flexibility.

As a robustness check, we also fit a model, including all control variables (Appendix Table E.1). This model increases the declared variance (R^2 = 0.172). The coefficients and significance of the cost and the social framing remain in the same range (9.24 %, $p = 0.026$ and -10.71 %, p=0.013). The impact of environmental framing is even smaller (0.71 %, $p = 0.847$) and still not significant. There are only two significant effects in the control variables: Participants with very high incomes (more than 3,500 Euros per month) are significantly less flexible (-13.07 %, p=0,008). Participants who consider themselves more willing to take risks are slightly more flexible (1.44 %, $p = 0.046$). The results remain stable even if we remove two outlier participants who never allowed flexible charging.

Table 9.4.: Regression table on the influence of framing messages on entered charging flexibility.

Variable	Coefficient	Std. Error	t-Statistic	P>|t|
Intercept [Control]	0.5856	0.026	22.573	0.000
Framing [Cost]	0.0876	0.040	2.184	0.030
Framing [Environmental]	0.0109	0.037	0.295	0.768
Framing [Social]	−0.0904	0.042	−2.134	0.034

Dep. Variable:	Charging Flexibility	**R-squared:**	0.088
Model:	OLS	**Adj. R-squared:**	0.071
Method:	Least Squares	**F-statistic:**	5.164
No. Observations:	164	**AIC:**	−86.86

9.5. Discussion

In this chapter, we identify framing messages as possible digital nudges to increase the charging flexibility of BEV users. Following the digital nudging development process of Mirsch et al. (2017); Weinmann et al. (2016), we conduct two studies to select and evaluate promising digital nudges. The results indicate that including framing messages in smart charging interfaces is a promising design approach to influence BEV users to charge flexibility.

Based on the theory outlined in Section 9.2 we interpret that the presentation of goal framing messages can influence the belief formation in terms of shifting in the users goals and which leads them towards more environmental-friendly actions, i. e., providing more charging flexibility. Therefore, goal framing seems to be a valuable design approach to influence human actions (compare Melville (2010)). This finding enables designers of smart charging systems to nudge users towards environmentally friendly charging behaviour and thus facilitates the successful integration of BEV into the energy system.

However, not all framing nudges show a positive influence in the experimental setting. If the cost framing is displayed to the participants, they show a higher charging flexibility. On the contrary, framings on the social aspects of the common use of shared resource, e. g., the electricity grid, reduced the entered flexibility. References to the integration of RES showed no influence compared to the neutral control treatment.

Interestingly, the effectiveness of the cost treatment contradicts the results in recent literature, e. g., Will and Schuller (2016), which does not find an influence of financial benefits. We assume that there are two possible explanations. First, because the survey stems from 2016, early adopters may have been more ecologically motivated than current BEV users in 2018. In particular, Will and Schuller (2016) do not control for environmental concern, which is a relevant driver of sustainable behaviour. A further explanation for the deviating results may lie in the difference in research design. Will and Schuller (2016) examine the arguments for smart charging in a within-subject design. On the contrary, in our experiment, different groups are presented with only one argument for smart charging. We assume that our participants are less influenced by effects such as social desirability compared to the study of Will and Schuller (2016).

The findings of Newman et al. (2012) could offer insights, why we could not observe a positive effect with an environmental goal framing. In their study, the authors show that the environmental concern mediates the influence of goal framing on sustainability behaviour, subjects with deep environmental concern should show a positive impact of the environmental framing massage. In contrast, participants with a low environmental concern should offer lower flexibility. In our sample, only six participants of the environmental framing group stated a low environmental concern, i. e., scoring lower than three on the scale from one to five. Moreover, the subjects offering the highest flexibility are more likely to show a medium-high than a very high environmental concern. Because of the limited data, it is difficult to interpret the slight positive correlation between environmental concern and offered flexibility. However, the mediating effect of environmental concern could provide some explanation for why environmental framing is very effective for some of the participants.

Many studies show the positive influence of social framing messages on energy conservation (Delmas et al., 2013). Remarkably, we find a negative effect of the social framing message on the charging flexibility. This effect could be because the cited studies were carried out within close neighbourhoods. In the online experiment, however, the perceived social presence was probably low. Low social presence could explain why we could not replicate the effect of normative framings in this experiment. Future experiment could examine the influence of social presence on the effectiveness of normative framings.

We further suspect that the social framing message did not only contain a normative message but was confounded with more information. The framing message read *'The power grid is shared with other users and benefits from the fact that they are flexible when charging their electric cars'*. The idea of a common and shared resource could have created the idea that the network is a scarce commodity and that the BEV would not be charged if the other users charged their BEV first which could trigger loss aversion (Schneider et al., 2017).

If this fear exists, the immediate reach entered by the participants in the social treatment should be higher than in the other groups while the final range is somewhat comparable. However, we find this effect only in the shopping scenario. This result contradicts this theory, as in the shopping scenario, the BEV does not need charging to make the next trip, and the need for setting high immediate range should be even lower than in the other scenarios. Also, in case of fear of a scarce resource, more risk-seeking participants should show greater flexibility in social framing treatment. However, we find no positive interaction between the social treatment and willingness to take risk.

In the experiment, only a few subjects remained with the default setting, which is often used as a powerful digital nudge (Momsen and Stoerk, 2014). This result raises the question, how well other digital nudges perform in the context of smart charging. As almost all participants were flexible in hypothetical settings, it is unclear how this transfers into the real world. In particular, because Delmas et al. (2013) conclude that monetary framings are not effective over a long period. If this applies to the context of smart charging, new ways are needed to make people stick with smart charging.

A main limitation of the study is that the result where not found in the field yet, but in an online experiment and thus, the external validity of the results may be impaired. However, since we designed the scenario setting as an onboarding situation, we are confident that the case in the online experiment is comparable to the real-world environment. Such an approach can be found in the literature mentioned above. However, we acknowledge that the results in the daily interaction with the smart charging system may be different, i. e., changing the charging setting immediately after connecting the BEV to the charging station. In this context, the decision situation may be different, and other nudges described above (such as defaults) may work even better. Field experiment could prove further insights in how to increase charging flexibility with digital nudges.

9.6. Conclusion

Beyond the context of smart charging, the results of the experiment raise two questions relevant to information systems, especially when it comes to developing information systems that influence human action towards more environmentally friendly behaviour (Melville, 2010).

First, since environmental framing works very well for a subgroup of participants, the question arises whether digital nudges should be designed to be adaptive and adaptable to the target group. Such adaptive nudges would require an understanding of which what objectives can motivate which users and easy to collect metrics to cluster the users into the right framing.

Secondly, we find a negative effect of social framing treatment. Further research could separate the normative and the goal framing messages to evaluate under what conditions BEV users react to normative framing and whether they are motivated by solving congestion in the grid. If the result confirmed the negative effect of normative framings, it would be interesting to analyse the differences between BEV charging and energy conservation, where the social nudges are effective. We suspect that the effect is mediated by spatial proximity or perceived proximity to peers.

Because the framings affect flexibility in different directions, designers and choice architects should be careful, which framing (messages) they use when designing smart charging systems. While pointing out to potential cost savings can increase the charging flexibility seems to be a framing that works for all users, environmental framing works well for some BEV users. In contrast, a social framing that represents the electricity grid as a scarce resource can even reduce flexibility.

Digital nudging and framing, in particular, could also increase the flexibility of the user against the user's interest, e. g., if the operator of a smart charging system retains the profit alone. This could even lead to situations, where the BEV users' mobility needs are impaired because they provide too much flexibility. If nudging results in such a disadvantage for the user or the objective of framing messages is not fulfilled, a discussion of the ethical dimension becomes necessary.

Another way to overcome problems with providing too much flexibility could be to implement learning components for smart charging systems that assist the BEV user in finding the right amount of flexibility. Based on the historic driving pattern, such systems could guide the BEV users decision when to charge flexibly and when the full charging power is required to reach the next destination. Chapter 11 proposes forecasts of charging flexibility allowing for such assistance.

Overall the results show that the careful design of charging systems will be crucial to integrate BEVs energy system and whether their impacts will be negative, e. g., causing grid congestion, or positive, e. g., fostering the integration of RES. As environmental objectives motivate some BEV users to charge flexibly, this could even lead to a self-reinforcing effect. If the smart charging system controls the charging session to integrate more RES it could provide the BEV users with feedback (i. e., a nudge) on the effects of their flexibility provision. This feedback nudge could motivate BEV users to provide even more flexibility. The following chapter proposes a forecast-based smart charging system that can provide such feedback.

Part IV.

Data Driven Smart Charging

CHAPTER 10

CO_2 EFFICIENT SMART CHARGING

This chapter is based on joint work conducted by Julian Huber, Kai Lohmann, Marc Schmidt, and Christof Weinhardt, currently under review in *Journal of Cleaner Production*, cited here as: Huber et al. (2020b). The working paper expands on the ideas and analyses published in Huber and Weinhardt (2018)

Greenhouse gas emissions of BEVs depend on the energy sources generating the electricity for charging. Depending in the merit-order the CO_2 emissions of BEV charging on the public grid vary over time. Smart charging offers the possibility to minimize carbon dioxide emissions by shifting the charging session to moments with lower emissions in power generation, e. g., times with high renewable generation (Jochem et al., 2015).

While BEV users usually have only limited knowledge and understanding about the energy system (Biresselioglu et al., 2018), the previous chapter shows that their willingness to charge flexibly (i. e., accept delayed charging) increases if the flexibility is used to integrate more renewable energies (Huber et al., 2019a). Even when BEV users are not experts on the energy system, they are more willing to use smart charging if it is used to minimize carbon emissions (Will and Schuller, 2016). In particular, CO_2 emission savings are higher the more flexible BEV users are with their charging (Huber and Weinhardt, 2018). Research on choice architecture shows that feedback on their energy consumption behaviour can nudge users to consume less energy (Mathur et al., 2018; Froehlich, 2009).

Similarly, direct feedback on the expected outcome of the action is a digital nudge that changes the decision environment and provides users with an understanding of their actions and could guide them towards more sustainable behaviour (see Chapter 7). Smart charging could implement such a feedback system in a smartphone application or charging station display. The display could provide the users with direct feedback on the expected CO_2 emissions of optimized charging based on the charging settings, i. e., how fast the users want their BEVs to charge.

To implement such a feedback system, the charging station operator requires a methodology to estimate the CO_2 saving potentials based on the charging settings in real-time. Additionally, the system should re-schedule the charging session to achieve forecasted emission savings.

CO_2 emissions in the energy system are volatile and differ based on the assessment methodology (Jochem et al., 2015). In result, providing feedback based on historical average values can result in both increased CO_2 emissions and far-off forecasts. For instance, a overly optimistic forecast could lead users to provide much flexibility, even when the system cannot save CO_2 emissions. For a discussion on the legitimacy of ethical nudging to increase sustainability see Kasperbauer (2017).

In summary, the feedback system requires a comprehensible method that returns the forecast of CO_2 emission savings for individual charging sessions in real-time.

Huber and Weinhardt (2018) first prose the idea of such a feedback and control system as a digital nudge. However, the system assumes perfect foresight and uses average emission factors (AEF). In this case, marginal emission factors (MEF) are more suited as they provide information on how the carbon emissions change for a change in load (Zivin et al., 2014).

In contrast, this chapter proposes a method to provide feedback and schedule smart charging in a way that avoids CO_2 emissions of an individual charging session using MEFs. We evaluate the system on data of the Germany energy market in 2017. The analysis of MEFs is based on historical generation data of German power plants with individual estimates for CO_2 efficiency and is calculated using the methodology by Hawkes (2010). Next, we develop a short-term forecaster for MEFs to estimate the emission factors during the charging session. Based on this forecast, we perform CO_2 minimizing charging strategies for different charging scenarios. In particular, we answer the following research questions.

First, we expect there are distinct patterns in the MEFs caused by reoccurring effects in the energy system (e. g., low emission in hours with high PV generation). Starting from here, we analyse the most promising situations for smart charging to save CO_2 emissions.

RQ 3 *At what time during the day can smart charging achieve the highest CO_2 emission savings?*

Second, we contribute to the discussion on using AEFs or MEFs for the evaluation of load shifting potentials. We hence answer the question:

RQ 4 *What are the absolute and temporal differences in CO_2 emission saving potentials assessed with average and marginal emission factors?*

Third, we compare the forecasted CO_2 saving feedback with the optimal solution to evaluate the performance of the scheduling algorithm.

RQ 5 *To what degree can a forecast-based system realize the CO_2 emission saving potentials of a perfect foresight scenario?*

The remainder of this chapter is structured as follows. Section 10.1 provides an overview of the related work regarding CO_2 emission factors and smart charging for RES integration. Next, we specify the input data and assumptions for the analysis in Section 10.2. Section 10.3 describes the methodology for deriving and forecasting the emission factors and the scheduling in smart charging. Section 10.4 presents the results of the analysis in the same order. We end the chapter with a discussion and of the results and a conclusion in Section 10.5 and Section 10.6.

10.1. Related Work

In the following, we present related work. Subsection 10.1.1 provides an overview of the calculation of different CO_2 emission factors and discusses their advantages and disadvantages. Next, Subsection 10.1.2 discusses the forecasting of such emission factors. Last, we discuss how emission factors have been used in smart charging.

The literature review has two starting points: First, we use the literature gathered by Fritz Braeuer in a newsgroup discussion on emission factors[1]. Next, we search two literature databases, i. e., Google Scholar, ScienceDirect, with different keywords (e. g., *'marginal CO2 emission factor'*, *'MEFs load shifting'*, *'marginal CO2 intensity forecast'*). The keyword search results in 30 relevant studies. Last, a backward or forward search from these matches produces more papers.

10.1.1. Emission Factors

Smart charging represents load shifting, where energy consumption is moved in time to obtain an optimization goal. In particular, we aim to shift the charging demand towards periods with low CO_2 emissions. Emission factors allow quantifying the minimization potential of emission savings from shifting electric loads (Ryan et al., 2016). CO_2 emission factors describe the amount of emissions emitted during the generation or consumption of an energy unit in gCO_2/ kWh (Zheng et al., 2015). Literature distinguishes two types of emission factors: AEFs indicate the CO_2 emissions attributed to an amount of energy, while MEFs indicate how the emission factor changes if an additional unit of energy is generated or consumed.

Olkkonen and Syri (2016) discuss what emission factor to consider in attributional and consequential life-cycle assessments. Attributional approaches evaluate emission in static energy systems and assign them to different generators or consumers (e. g., using AEF). For analyzing the environmental impact of a future change in demand structure, however, a consequential life-cycle assessment is required. In the case of smart charging, using MEF considers the effect of future load shifting on the energy system (Regett et al., 2018).

Besides attributional and consequential analysis, Yang (2013) provides two temporal dimensions to differentiate emission factors: First, emission factors can be broken down into different temporal resolutions. For instance, when analyzing the effects of load shifting in smart charging, the resolution should be high enough so that there are observable differences in the emission factors during the charging session. Next, the analysis of emission factors can have a retrospective or forward-looking perspective. In this use case, the perspective is forward-looking, as the scheduling process requires a forecast of the emission factors.

[1] Email by Fritz Braeuer of 02.08.2018, available after registration at `www.strommarkttreffen.org/`, last accessed on 19.01.2019

Average Emission Factors AEFs are the ratio of emissions to energy generated in a given period. For instance, Doucette and McCulloch (2011) use AEFs to attribute CO_2 emissions caused by BEVs in several countries to compare them with emissions from vehicles with ICE. They acknowledge that MEFs would be more suitable for their consequential assessment, but discard them because of the higher calculation effort. Bickert et al. (2015) use AEF to compare environmental and economic potentials of small electric and combustion engine vehicles but do not discuss their choice. Likewise, Huber and Weinhardt (2018) propose a CO_2 feedback system to incentivize smart charging based on AEFs. When providing feedback to the end-user it might be easier to explain that there are times with higher and lower emissions in the energy system (i. e., an attributional approach with AEF) than what would hypothetically happen if they shifted their load (consequential approach with MEF). However, the attributional approach does not reflect the actual effects resulting from smart charging. Jochem et al. (2015) analyse the CO_2 emissions of BEV based on different assessment methods. They evaluate the emissions based on the annual average mix (i. e., AEF) and marginal electricity mix (i. e., MEF), without considering the timing of BEV charging during the evaluation year. To cover such temporal effects, they also calculate the time-dependent average mix. Further, they consider a zero-change scenario based on the notion of the EU Emission Trading System.

Marginal Emission Factors MEFs describe the change in emission when the system load is incremented or reduced by one unit (Zheng et al., 2015; Hawkes, 2010). As load shifting reduces the system load at one point in time and moves it to another, the MEFs should be used to account for avoided emissions (Ensslen et al., 2017; Eßer and Sensfuß, 2016; Li et al., 2017; Siler-Evans et al., 2012). Likewise, they are the basis for consequential assessment of the impact of additional demand (e. g., BEVs) in a system (Doucette and McCulloch, 2011).

As the results of the assessment can vary strongly between different methods, the use of AEFs can lead to misleading results, misinform decision-makers, and lead to wrong interventions (Siler-Evans et al., 2012).

Literature provides two approaches to determine the MEFs of an energy system (Zheng et al., 2015; Ryan et al., 2016). The first method is based on electricity market models. Electricity market models allow to model the dispatch of the power plants and thus determine the last generation unit in the merit order that would react to a change in load. In this case, the MEF is defined as the emission factor of the last generation unit. However, due to other restrictions, the most expensive power plant is not necessarily the marginal power plant (Dandres et al., 2017). Such confusion would result in misleading MEFs. As a benefit, such models can consider fundamental changes in the power system and are often used for long-term assessments in contrast to statistical methods based on historical data.

For instance, McCarthy and Yang (2010) use cost-based merit order models for the Californian energy market and find that the MEFs exceed the AEFs at most points in time. Thomas (2012) use the same approach for all US regions and find that BEV with uncontrolled charging could increase carbon emissions when replacing ICE vehicles. In a study on the long-term effects of BEV integration in the German energy market up to 2030, Jochem et al. (2015) find that switching from ICE to BEVs will not naturally avoid CO_2 emission in case of uncontrolled charging. As smart charging can reduce CO_2 emission compared to uncontrolled charging, the authors call for measures to incentivize smart charging. For specialized assessments, some research also expands merit order models to temporal and regional effects. Olkkonen and Syri (2016) consider imports and exports while Zheng et al. (2015) focus on the start-up restrictions of power plants. When assessments rely on a full model of the analysed energy system, they are well suited to analyse the effects of fundamental changes in these systems (e. g., integration a higher share of RES or a large number of new consumers such as BEVs).

A second approach avoids modelling the merit order explicitly. In this approach the MEFs are estimated by an evaluation of historical, empirical data. If there are no significant changes in the energy systems during the assessment period, the analysis of empirical data can produce estimates of MEFs. Hawkes (2010) proposes a regression-based methodology to calculate the MEFs for Great Britain that is used by many subsequent studies (Thomson et al., 2017; Holland and Mansur, 2008; Holland et al., 2015; Staffell, 2017). In this approach, at each time step, the change in the system's emissions is explained with the change in system load. This relationship allows estimating the marginal emission for different states (e. g., load levels) of the energy system.

Siler-Evans et al. (2012), Li et al. (2017), and Thind et al. (2017) apply the model to American electricity markets. Siler-Evans et al. (2012) expand it for other emission factors (i. e., nitrogen oxides (NO_x) and sulphur dioxid (SO_x)). A further expansion by Siler-Evans et al. (2012) is to include non-emitting power plants such as nuclear power plants and renewable energy plants. They argue that with the increasing share in the electricity generation portfolio, they also are more likely to be part of the last generators in the merit order that influences the MEFs.

To analyse the effects of smart charging, Pareschi et al. (2017) apply the methodology for the German and Swiss electricity market. They find that BEVs can contribute substantially to CO_2 emissions, even in a low emission energy system (i. e., Switzerland) if cross-border flows are considered.

Such assessments based on historical data are suitable for short-term considerations but rather unsuitable for long-term studies. With a long time horizon, structural changes, e. g., in the infrastructure, may occur that are not taken into account by the determined emission factors (Thind et al., 2017). As an advantage, the regression approach implicitly consideres the power systems characteristics (e. g., market power, transfer and other restrictions) that would have to be modelled otherwise (Graff Zivin et al., 2014; Siler-Evans et al., 2012). Besides, they are easier to compute and transparent compared to system models and simulations (Yang, 2013). For this reasons, a regression-based approach is well suited for a short-term analysis in a real-time feedback system.

10.1.2. Short-Term Forecasting

Besides historical MEF, a load shifting system requires a short-term forecast of the MEF to schedule charging in a CO_2 saving fashion. To our knowledge, literature does not provide a forecast of short-term MEFs (e. g., to provide customers with real-time information on the optimal charging strategy). Such a forecast can result from models of the future merit order or, in case of a regression-based assessment, from a forecast based on historical data. While there is no short-term forecast of MEFs, Lowry (2018) generates short-term AEF forecasts. Besides lagged actual values of AEF they do not use any external variables.

As the regression models relies on a system's load level, short-term MEF-forecasts can utilize short-term load forecasts. Short-term forecasts cover a forecasting horizon from several minutes to days and can be classified into time series and causal models (Hippert et al., 2001).

time series models include auto-regressive models or models based on Kalman filters. Causal models include box Jenkins, linear regressions, or ARMAX models. As the load is not linearly dependent on exogenous variables, machine learning models (e. g., artificial neural networks) are applied to find and use these relationships. Khan et al. (2016) show that methods of machine learning for short-term load forecasting can significantly improve the accuracy compared to simple statistical models. Short-term load forecasting can rely on extensive literature with different models and exogenous variables (Charytoniuk et al., 1998; Hagan and Behr, 1987; Huang and Shih, 2003; Chow and Leung, 1996).

10.1.3. Smart Charging

CO_2 emission factors are the basis of life-cycle assessments of BEVs (Ma et al., 2012) especially when compared to cars with ICE (Onat et al., 2015; Yuksel et al., 2016)

Smart charging literature does not only consider saving CO_2 emission, but many other objectives (Huber et al., 2019b): For instance, peak shaving (Druitt and Früh, 2012), cost minimisation for drivers (Hahn et al., 2013; Cao et al., 2012), and charging station operators (Weis et al., 2015).

Schuller et al. (2015) propose a charging schedule to maximize the share of RES in the electricity mix, but do not evaluate emission savings. However, other studies research the CO_2 saving potentials of load shifting: Huber and Weinhardt (2018) determine CO_2 saving potential of individual charging sessions based on hourly AEFs. Hoehne and Chester (2016) use regionally and temporally differentiated MEFs of Siler-Evans et al. (2012) to investigate the CO_2 saving potential in the short-term optimized control of charging sessions and find a savings potential of 31 % compared to pre-planned loading plans under standard conditions. Short-term MEFs are also used for other applications of demand-side management, e. g., storage technologies (McKenna et al., 2017) or data centres (Dandres et al., 2017). However, these evaluations do only analyse the potential under prefect foresight based on historical data and do not prose a real-time system.

For long-time analysis, Kim and Rahimi (2014) use a dispatch model to determine MEFs and to analyse the effects of aggregated load shifting. Jochem et al. (2015) consider controlled charging for the year 2030 on an aggregated level and compare both AEF and modelled MEFs.

The related work shows that MEF can be used to evaluate short-term CO_2 saving potentials of load shifting (Hoehne and Chester, 2016). However, the existing approaches do not account for uncertainty when forecasting future emission factors. Evaluating the saving potentials requires a time series of the MEFs. For a short-term analysis, MEF time series can be evaluated with a data-based approach (Hawkes, 2010). The data basis is described in the following chapter.

10.2. Data

The estimation of MEFs requires an energy system model or an extensive database of data of real energy systems. This section presents the data used to estimate the MEFs for Germany based on the regression approach by Hawkes (2010). All the pre-processed data sets and calculations are available at Lohmann et al. (2019). In particular, the estimation of MEFs relies on the electric emission factors of each power plant (i. e., the power plants electric efficiency and the fuels emission factor) and their generation. Besides, we use weather data to improve the forecast of the system load and MEFs.

10.2.1. Fuel-specific CO_2 Emission Factors

Oxidation breaks down carbon-based fuels into H_2O and CO_2 (and other compounds) and generates thermal energy. As some fuels have a higher ratio of carbon atoms compared to bindings, they result in a higher number of CO_2 molecules while generating the same amount of thermal energy. This relation is described by the fuel-specific CO_2 emission factor in g/J. Like Ensslen et al. (2017), we rely on the data of the Germany Federal Environment Agency (2018, p. 833 f.). Table 10.1 shows the fuel-specific CO_2 emission factors used for this work. These emission factors are the net emission factors which only account for the emissions released during combustion. They do not consider up- or down-stream process emissions. We only consider fuel types relevant in the power plant-specific generation data for Germany by ENTSO-E (2019b) described in the following section.

Table 10.1.: Thermal CO_2 emission factors for different generation technologies and fuels.

Fuel / Technology	CO_2 Emission Factor [gCO_2/ kWh_{th}]
Lignite Rhineland	407
Lignite Middle Germany	374
Lignite Lusatia	401
Hard Coal	337
Natural Gas	201
Fuel Oil	280
Other Fossiles	424
Waste	329
Hydro	0
Nuclear Power	0

10.2.2. Power Plant Efficiency

Power plant efficiency describes how much electrical energy a thermal power plant produces for an input of one thermal energy unit. Estimates for power plant efficiencies in Germany are available at the Open Power System Data project (OPSD, 2018). The project provides list of conventional power plants in Germany based on data from Bundesnetzagentur (2018) and Umweltbundesamt (2019).

The data contains 226 power plants with a generation capacity beyond 100 MW_{el}. Ninety of the power plants have a researched efficiency. The efficiency of the remaining power plants is estimated based on Egerer et al. (2014) using a linear function of the technology and the year of construction.

The mean deviation of the estimated values from the researched values is 2.6 percentage points. To keep things consistent, we decide for using only estimated values, even if the researched values for the individual power plants might be more accurate. There is no data for plants operated with *'other fossil gases'*. For these plants, we use the mean values for natural gas power plant[2].

[2] Steam turbine: 36,9 % Gas and steam: 53,5 %

10.2.3. System Load and Generation

ENTSO-E (2019a) provides system load and generation data for power plants beyond 100 MW_{el} in a temporal resolution of 15 minutes. To link the load data with the emission data, we aggregate to hourly values by calculating the mean value.

10.2.4. Weather Variables

The weather data for the load forecasts includes the air temperature in hourly resolution for 78 measuring stations in Germany (Deutscher Wetterdienst, 2019). We use the values of the stations in Stuttgart, Berlin, Dusseldorf and Nuremberg as an input to the load forecast to cover different regions in Germany. The selection of these four stations is arbitrary and does not follow a specific framework, e. g., Hong et al. (2015). We omit a more sophisticated approach as the forecast is not in the focus of this work and we find no strong correlation of temperature variables with the German load.

10.3. Methodology

This chapter discusses the methodology used to answer the research questions. Figure 10.1 describes the methodology in a flow chart. After gathering and preprocessing the data for Germany in 2017, we calculate the AEF and MEFs based on a linear regression model. Next, we generate a forecast for the MEFs. Last, we optimize charging based on these forecasts and determine the emission saving potentials.

10.3.1. Plant-Specific Emission Factors

Using emission factors on power plant level aims to improve the accuracy of subsequent analyses compared to using technology-specific emission factors currently applied in the literature (Hawkes, 2010). The plant-specific emission factor γ^p in gCO_2/ kWh_{el} of a power plant p, using a fuel type k, depends on the fuel-specific emission factor γ^k and the electric efficiency of the power plant η^p:

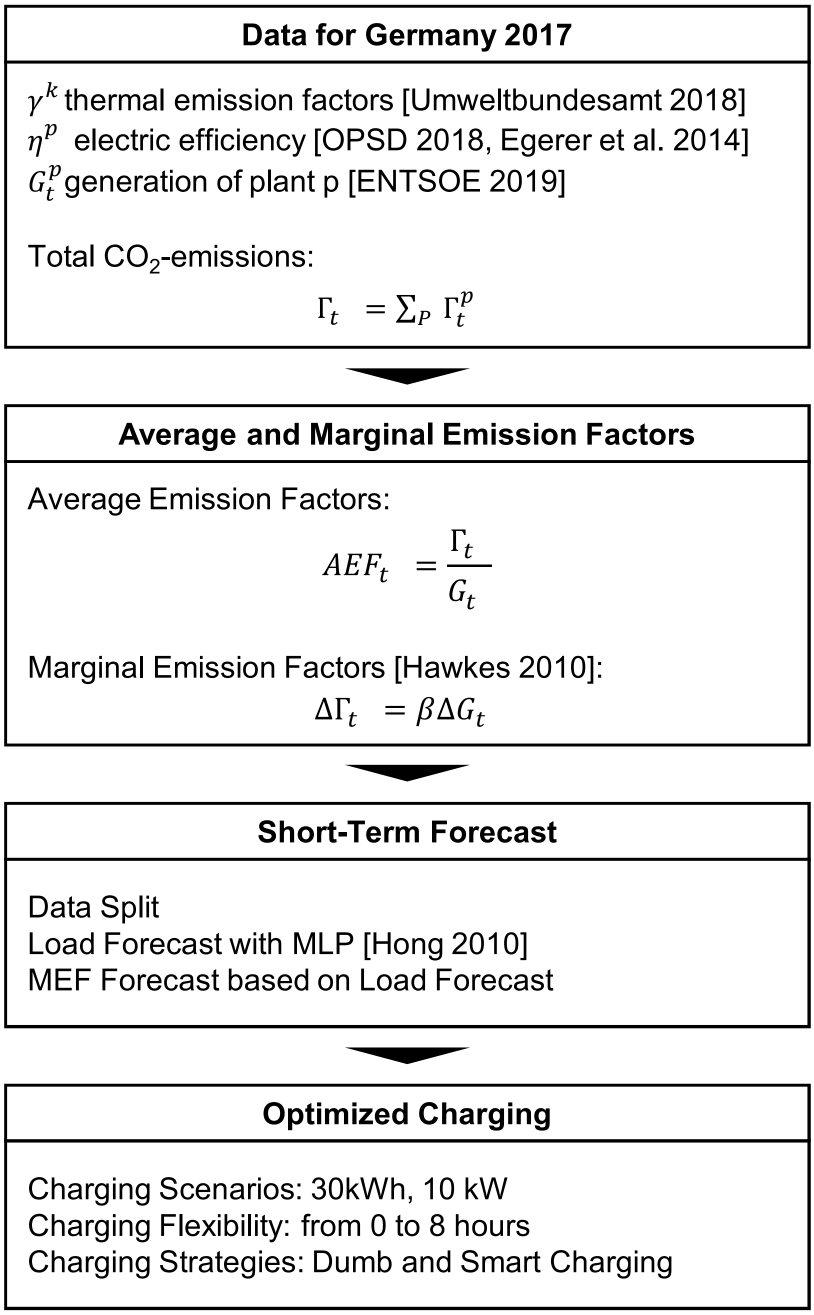


Figure 10.1.: Flow chart of the evaluation process for CO_2 efficient smart charging.

$$\gamma^p = \gamma^k \cdot \eta^p. \tag{10.1}$$

The specific emission factor γ^p of a power plant and its hourly generation G_t^p result in its absolute CO_2 emissions Γ_t^p:

$$\Gamma_t^p = \gamma^p \cdot G_t^p. \tag{10.2}$$

Table 10.2 shows the specific emission factors calculated on plant-level data averaged by technology and in comparison to Ensslen et al. (2017). Note that the table aggregates different lignite specifications and that the definition of the individual technologies in this work and the literature reference may not follow the same definition as in the related work. For instance, Ensslen et al. (2017) do not provide values for waste or other fossil gases). Apart from fuel oil, all technologies are on similar levels.

Table 10.2.: Comparison of average fuel-specific electric CO_2 emission factors based on own calculations of plant-specific thermal efficiencies.

	Electric CO_2 Emission Factor $[g/\ kWh_{el}]$			
	This Work			Ensslen et al. (2017)
Technology	Mean	Max	Min	Mean
Lignite	1,082	1,288	935	1,160
Hard Coal	832	1,014	729	905
Natural Gas	410	594	328	377
Fuel Oil	778	857	731	571
Other Fossile Gases	971	1149	793	-
Waste	997	997	997	-
Nuclear	0	0	0	0
Hydro	0	0	0	0

10.3.2. Average Emission Factors

The AEFs provide a benchmark and allow answering RQ 4. We use the system-wide AEFs to enable a comparison with Huber and Weinhardt (2018). The system-wide AEF_t is calculated based on the net emission factor γ^k of the technology k and the share s_t^k of the technology k of the total generation in hour t:

$$AEF_t = \sum_K (\gamma^k \cdot s_t^k). \tag{10.3}$$

We assign the subgroups in technologies in ENTSO-E (2019c) to superordinate categories in Table 10.2. RES (i. e., wind, solar, and biomass) are assumed to have a CO_2 emission factor of $0\,gCO_2/\ kWh_{el}$.

Note that the power plants in this calculation differ from the power plants used to determine the MEFs. The AEFs consider all power plants (in particular, wind and solar plants) and plants with generation capacity below 100 MW. The shares s_t^k are based on the generation data by technology described above.

10.3.3. Marginal Emission Factors

We calculate the MEFs according to the methodology of Hawkes (2010) using a linear regression model. In the following, we discuss the methodological steps and decisions in determining the MEFs. This description includes the calculation of the system's emission factor and load, choice of the regressor, splitting the time series, and the analysis of the marginal mix.

Linear Regression of Marginal Emission Factors

The estimation of MEFs using linear regression model depends on assumptions during the modelling process. In particular, the estimated MEF change with the sharpness of emission factors (i. e., whether technology or power plant-specific emission factors are used). Next, they depend on the choice of the explanatory variable of the regression model (i. e., system load, residual load, or generation). Last, they are affected by the geographical and temporal resolution of the analysis and the grouping of data in different temporal or systematic groups with separate regression models. We unfold our considerations and decisions on these assumptions in the following paragraphs.

The regression model explains the hourly change of the system's CO_2 emissions with the hourly change of its conventional generation (Hawkes, 2010; Siler-Evans et al., 2012). We fit the regression model based on aggregated hourly emission values of the energy system (i. e., all power plants) and the conventional generation

(i. e., residual load) in Germany for the year 2017. We only consider CO_2 emissions, other greenhouse gases or equivalents are not considered.

The hourly generation G_t and the hourly emissions Γ_t are the sums of the respective values of the individual power plants p (Formula 10.4 and 10.5):

$$G_t = \sum_P (G_t^p). \tag{10.4}$$

$$\Gamma_t = \sum_P (\Gamma_t^p). \tag{10.5}$$

Subsequently, Formula 10.7 and 10.8 result in the hourly changes in the generation ΔG_t and the CO_2 emissions $\Delta\Gamma_t$ for each hour of the year. The linear regression model (Formula 10.6) with the slope β describes the hourly change in CO_2 emissions with the hourly change in generation.

$$\Delta\Gamma_t = \beta \cdot \Delta G_t + \epsilon, \tag{10.6}$$

where

$$\Delta\Gamma_t = \Gamma_t - \Gamma_{t-1}, \tag{10.7}$$

and

$$\Delta G_t = G_t - G_{t-1}. \tag{10.8}$$

The slope in the regression model β in Figure 10.2 is interpreted as the average MEF (i. e., the historical change in emissions given a change in conventional generation). The y-axis section of the regression line is set to zero to obtain unique and comparable slope values (Li et al., 2017).

Selection of Power Plants

The MEF should only consider power plants that are marginal generators because these are the ones that react to load shifting (i. e., power plants that adapt their generation in reaction to load changes). These are usually the most expensive power plants. In contrast, a power plant with low operational costs such as renewable energies or nuclear power plants should not be marginal generators (McCarthy and Yang, 2010). Likewise, power plants whose generation naturally fluctuates (i. e., RES) and does not react to changes in demand are not part of the marginal mix. Li et al. (2017) provide an in-depth discussion of which generators to consider.

Most of the literature only considers conventional power plants (Hawkes, 2010; Siler-Evans et al., 2012; Graff Zivin et al., 2014). Consequently, we use the conventional power plants included in the ENTSO-E (2019a) data set which does not include wind, solar, and biomass power plants.

As a sensitivity analysis, we also used other power plants for the estimation of MEF. The results of this analysis are noted in Table 10.3. The first row represents all the power plants from the ENTSO-E (2019a) data set. The second row omits pumped storage power plants, while the third row only includes coal and gas power plants. Pumped storage power plants have an emission factor of zero and have a significant change in their generation patterns. These effects result in higher average MEFs (i. e., β in Table 10.3) for regressions without pumped storage power plants (row 2 and 3). As pumped storage power plants are not subject to natural fluctuation but react as peak load power plants to changes in demand, we consider them relevant in the analysis.

Table 10.3.: Sensitivity of marginal emission factors β in tCO_2/ kWh_{el} for different generation technologies in the considered generation.

Considered Technologies	R^2	β
Lignite, Hard Coal, Natural Gas, Fuel Oil, Other Fossil Gases, Waste, Nuclear, Hydro, Pumped Storage	0.84	0.54
Lignite, Hard Coal, Natural Gas, Fuel Oil, Other Fossil Gases, Waste, Nuclear, Hydro	0.97	0.73
Hard Coal, Natural Gas	0.99	0.69

The MEFs describe a change in emissions with the conventional generation (i. e., regressor in the regression model). Literature names both, the system load and the conventional generation, as possible regressors. If the total generation covers the total system load (i. e., ignoring imports and exports), the system load corresponds to the generation.

In this chapter, we use the hourly generation of the selected power plants as the regressor. The generation of these power plants also represents the residual load (i. e., the system load less the feed-in of fluctuating producers[3]). This decision is based on the following notion:

Only those generators which react to load changes are relevant for consideration of marginal power plants. In contrast, we do not aim to consider generators with a natural fluctuation independent from changes in load. As we focus on the load changes that are not covered by natural factors, we use the generation of conventional and hydro power plants as a regressor. Otherwise, the analysis would also include the effects of changes in emissions that are not related to the changes in connected load (i. e., potentially shifted charging).

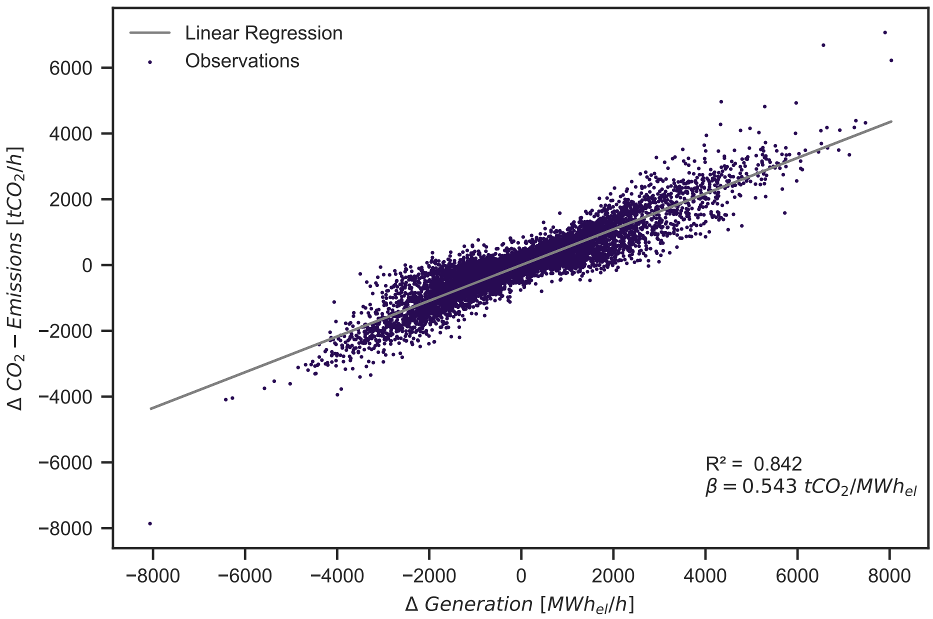


Figure 10.2.: Linear regression for system-wide CO_2 emissions $\Delta\Gamma_t$ and change in residual load ΔG_t with marginal emission factor β considering lignite, hard coal, natural gas, fuel oil, other fossil gases, waste, nuclear, hydro, and pumped storage.

[3]We also omit biomass power plants and power plants with a nominal capacity of less than 100 MW.

Marginal Emission Factors for different Load Levels

Figure 10.2 resembles a single MEF for the full year of 2017 (i. e., each observation the hourly change throughout this year). As the status of the energy system changes over time, there are different approaches to evaluate MEFs in greater detail. Different load levels represent a different dispatch in the merit order, it is common to evaluate the MEFs for different load levels (Hawkes, 2010; Siler-Evans et al., 2012; Li et al., 2017). In this case, the regression is fitted separately for each load level and the slope of the regression is interpreted as the average MEF for the specific load level. Consequently, the resulting MEFs depend on the definition of load levels. One way is to split the data in quantiles so that each range contains the same number of observed system load points. While this split guarantees that the regression can rely on a sufficient number of data points, a quantile could cover a broad range of values resulting in unstable results. Alternatively, load data can be divided into ranges with a fixed width. However, these ranges could be sparse containing only a few data points resulting in similar problems.

When splitting the data, there is a trade-off between a more differentiated MEF image and the stability of the regression models. A higher number ob quantiles leads to a more refined picture, but can lead to instability in the results due to fewer data points in each range. In this chapter, we follow Hawkes (2010) and Siler-Evans et al. (2012), which use 5 % quantiles resulting in 20 load ranges. The use of 5 % quantiles ensures a sufficient number of data points for regression in all ranges. We compose the time series of MEFs based on the system load assigning each hour of 2017 to a 5 % load quantile and the corresponding MEF (see Figure 10.3).

Marginal Mix

The marginal mix describes the composition of marginal power plants at a certain point in time. These are the power plants that show a change in generation compared to the previous hour. In particular, the marginal mix at a certain time or load range helps to explain the level of the MEFs in this particular situation. For example, times when fossil power plants ramp-up show large MEFs. However, the characteristics of the marginal mix depend on the definition and following calculation procedure (Siler-

Evans et al., 2012; Li et al., 2017):

Absolute changes in generation can be added up at technology or plant level. If added on plant level, opposed changes in individual generation technologies (e. g., in coal power plant ramping up, another reducing load) would result in a small change in the system load but high changes in coal-generation. This effect can result in very large shares of the specific technologies in the marginal mix. The effect can be avoided by summing the absolute values of changes on technology level. As using technology-level evaluation helps to explain the MEFs, we use the absolute changes on technology level in relation to the sum of all changes. In this way, the visualisation in Figure 10.5 explains the composition of the marginal mix but does not show whether technologies behave positively or negatively towards the total change in generation.

10.3.4. Short-Term Forecast for Marginal Emission Factors

To derive, short-term forecasts for marginal emission factors, we follow Hong (2010), who uses a three-layer feed-forward multi-layer perceptron (MLP) for short-term load forecasts. As there are no simple rules to determine the optimal number of neurons in the hidden layer (Hong, 2010), we use a grid search between 5 to 50. We decide on a forecast horizon of eight hours to cover the average duration of a parking event (compare Chapter 5 and 11). There are two possibilities to forecast eight hours into the future. Each hour can be forecasted by a single MLP with eight output neurons or eight MLPs with one output neuron. We use the second option, as smaller MLPs are more robust against over-fitting (Hippert et al., 2001). As input variables, we use essential parameters from (Hippert et al., 2001; Hong, 2010): historical load data, temperature data, and calendar information.

Based on the auto-correlation function, we use the last two values before the forecasting horizon and the load one day and one week before the forecasted hours as inputs.

We implement the MLP using the implementation by Seabold and Perktold (2010) and follow the default settings in all but the following properties. The activation function is a rectified linear unit recommended by Goodfellow et al. (2016). The solver (*adam*) stops at 1000 iterations or reaching a stopping criterion.

First, we split a 20 % test set from the data by sampling 8-hour splits from the data. We omit a rolling cross-validation to obtain results for the whole year. Doing so, we break the temporal integrity of the data. However, Bergmeir and Benítez (2012) show that this has no adverse effect on out-of-sample performance in practice. On the remaining 80 % of the data, we perform a shuffled 5-fold cross-valdiation used in the grid search for selecting the best model by minimizing the MAPE. MAPE is the standard accuracy measure in load forecasting (Hong, 2010; Tripathi et al., 2008):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \mid \frac{y_t - \hat{y}_t}{y_t} \mid \cdot 100\%. \tag{10.9}$$

As MAPE is undefined if $y_t = 0$ it should not be used in time series that have values of zero (Hyndman and Athanasopoulos, 2018). However, zero values doe not occur in Germany's system load.

We compare the MLPs performance with two naive benchmarks adapted from Hyndman and Athanasopoulos (2018). First, we use the values of the forecast origin for the next eight hours:

$$\hat{y}_{t_0+[1,8]} = t_0. \tag{10.10}$$

Second, we use the observation one week before as a naive seasonal forecast for each hour:

$$\hat{y}_t = y_{t-168}. \tag{10.11}$$

Finally, we create the MEF forecast assigning the predicted load levels to MEFs using the quantile from estimating the MEF.

10.3.5. Optimized Charging

Finally, we apply the forecast to minimize CO_2 emissions during smart charging. The flexibility and potentials of load shifting dependend on charging power, energy demand, and time constraints (Babrowski et al., 2014). We model these parameters based on Huber and Weinhardt (2018) and Petersen et al. (2013).

As before, we use a discrete model with time steps $\bar{t}$. Each charging session' earliest start is at time of arrival t^a when the BEV connects to the charging station.

The charging session ends no later than the time of departure t^d. The time between connection and departure is the parking duration d of the charging session:

$$d = t^d - t^a. \tag{10.12}$$

During this time, the charging load C_t is limited by the maximum charging power $\dot{C}$. Further constraints are the battery of the electric vehicle with a maximum energy capacity W^{max} and state of charge SoC_t.

The required or desired amount of charged energy at the end of charging W^{t^d} is equals the difference of initial state of charge SoC^a and SoC^d:

$$W^{t^d} \leq (1 - SoC^a) \cdot W^{max}. \tag{10.13}$$

The incremental amount of energy charged during a time step w_t is limited by the maximum charging power and the temporal resolution. The charging energy for each time step w_t is the decision variable of the smart charging problem. In contrast, dumb charging at $\dot{C}$ results in the shortest possible charging duration δ^{min}:

$$\delta^{min} = \frac{W^{t^d}}{\dot{C}}. \tag{10.14}$$

We define, the temporal flexibility ζ^{temp} as the difference in parking duration and the shortest possible charging duration:

$$\zeta^{temp} = d - \delta^{min}. \tag{10.15}$$

The total emissions during a charging session Γ^{AEF} and Γ^{MEF} depend on the emissions for each time step γ_t^{AEF}, γ_t^{MEF}, the energy demand and the temporal flexibility.

To answer the research question, we compare the emission of two charging strategies: Direct and uninterrupted (dumb) charging Ψ^u at the maximal charging power starting at time of arrival has a ζ^{temp} of zero causes the following emissions:

$$\Gamma = \sum_{t=t^a}^{t^a+\delta^{min}} (\bar{t} \times \gamma_t \times \dot{C}) \tag{10.16}$$

The smart charging strategy Ψ^s to minimize the CO_2 emissions has the following optimization problem:

$$\begin{aligned} \min_{w_t} \quad & \Gamma = \sum_{t=t^a}^{t^d} (w_t \times \gamma_t) \\ \text{s.t.} \quad & w_t \leq \bar{t} \times \dot{C} \\ & \sum_{t=t^a}^{t^d} w_t = W^{t^d} \\ & w_t \geq 0. \end{aligned} \tag{10.17}$$

Table 10.4.: Evaluation scenarios with different charging strategies and underling emission factors.

	Dumb Charging	Smart Charging
AEF	$\Psi^{u,AEF}$	$\Psi^{s,AEF}$
MEF	$\Psi^{u,MEF}$	$\Psi^{s,MEF}$, $\hat{\Psi}^{s,MEF}$

To answer the research questions, we calculate five different scenarios based on the charging strategies noted in Table 10.4. First, we create ground truth data for AEFs and MEFs using perfect foresight. Thereby, we use both strategies resulting in four different scenarios ($\Psi^{u,AEF}$, $\Psi^{s,AEF}$, $\Psi^{u,MEF}$, $\Psi^{s,MEF}$). Besides, we use scheduling based on the forecast to evaluate the performance of the real-time feedback system with scenario $\hat{\Psi}^{s,MEF}$.

The comparison on the scenarios allows to answer the research questions. RQ 3 evaluates the CO_2 saving potentials of smart charging, by comparing the emissions of dumb and smart charging based on the emissions in scenario $\Psi^{u,MEF}$ and $\hat{\Psi}^{s,MEF}$. A comparison of the saving between smart and dumb charging with AEF and MEF ($\Psi^{u,AEF}$ and $\Psi^{s,AEF}$) and ($\Psi^{u,MEF}$ and $\Psi^{s,MEF}$) answers on the differences of considering different emission factors (RQ 4). Last, we evaluate RQ 5 by comparing the saving potentials with perfect foresight ($\Psi^{u,MEF}$) with the performance of the real-time feedback system ($\hat{\Psi}^{s,MEF}$).

As the data used has an hourly resolution, we also use time step of $\bar{t}$ of one hour in optimizing the charging. Hence, each smart charging strategy Ψ^s can be interrupted for each hour during the charging period h. Our assumptions on the charging session follow Huber and Weinhardt (2018) and Schuller et al. (2015) to obtain comparable results. The desired amount of energy at the end of charging W_{t^d} is 30 kWh and the maximum charging power C_{max} is 10 kW. To evaluate the saving potentials of individual charging sessions throughout the year, we do not make further assumptions on the charging behaviour.

The idea is to generate direct feedback and decisions for the users at the start of the charging session, the optimization runs on the start of the charging session t^a. After that point, we do not generate new optimized forecasts or use online-optimization.

10.4. Results

In this section, we discuss the results of the methodology. First, we present the estimated MEFs for Germany in 2017. In Subsection 10.4.2, we describe the performance of the short-term forecasts. Last, we evaluate the CO_2 saving potentials of the smart charging sessions.

10.4.1. Marginal Emission Factors for Germany in 2017

The regression model results in an average MEF for 2017 of 550 gCO_2/ kWh_{el}. This is around 17 % higher than the system-wide AEF, based on the entire generation mix (469 gCO_2/ kWh_{el}). As the results depend on the characteristics of the energy system, they are difficult to compare with other studies from the US or UK: For example, the MEFs exceed the AEFs in Bettle et al. (2006) by up to 50 %, Siler-Evans et al. (2012) determines differences of -25 % to +35 % depending on the region. An analysis for Germany by Pareschi et al. (2017) using the same methodology (Hawkes 2010) finds average MEF of 760 gCO_2/ kWh_{el}. As they do not reveal all assumptions, especially the power plants used, there is no way in explaining the differences. Jochem et al. (2015) use a energy system model, to determine MEFs in Germany in 2030 and find MEFs of 550 gCO_2/ kWh_{el}.

Figure 10.5 shows the average MEF depending on the system load for 20 load quantiles. The MEF shows a negative correlation with increasing load level. The highest MEF is at the lowest load level[4] at 729 gCO_2/ kWh_{el}. In the highest load range[5] the MEF is 343 gCO_2/ kWh_{el}.

[4] Average load value of the lowest load range: 37 gigawatts (GW)
[5] Average load value of the highest load range: 75.5 GW

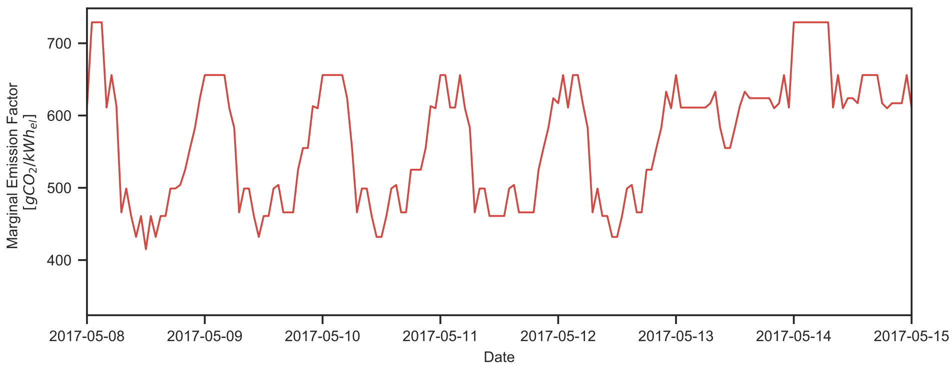


Figure 10.3.: Exemplarily time series of marginal emission factors in May 2017.

Regett et al. (2018) names this finding the merit order dilemma of emissions: Power plants with a high emission factor have lower marginal costs and are dispatched at lower load levels.

There are only minor changes in average MEFs between the months of the year (i. e., spreads of 74 gCO_2/ kWh_{el} in different months compared to spreads of 386 gCO_2/ kWh_{el} in different load levels. There is no clear pattern throughout the year with the highest values in March, June, November.

Changes throughout the day are higher and more relevant for the potentials of smart charging. Figure 10.4 compares AEFs and MEFs depending on the time of day. Averaged MEFs are higher than the AEFs for all times of the day but show high correlation. The low system load in the night hours result in higher MEFs with values of over 600 gCO_2/ kWh_{el} between 11 p.m. and 5 a.m. The AEF curve has values around 500 gCO_2/ kWh_{el} in the evening and night hours and drops to 400 gCO_2/ kWh_{el} during the day due to solar generation.

Figure 10.5 shows the marginal mix based on relative changes in technology, the MEFs, the AEFs in relation to the load level. The decrease in MEFs with increasing load level results from a higher proportion of lignite and hard coal in the marginal mix at low load levels (compared to higher levels). At high load levels pumped storage and natural gas increase generation leading to a decline in MEFs. The AEFs do not change much as the share of technologies in total conventional generation does not change much, and the effects cancel each other out. Figure 10.5 shows a shrinking share of nuclear power having zero emissions and lignite with high emissions

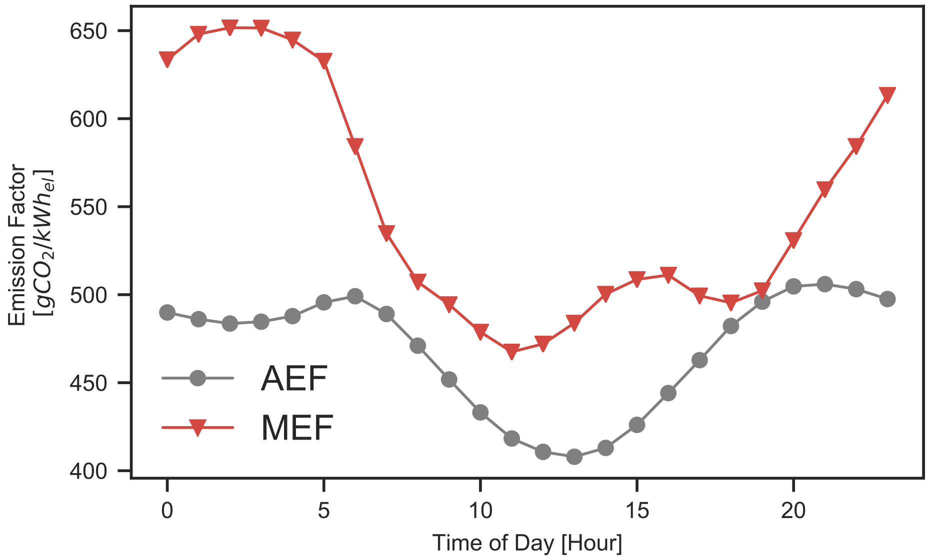


Figure 10.4.: Hourly average of average and marginal emission factors in Germany 2017.

with higher load levels. The change in emissions is compensated with an increase in generation from hard coal and RES. The composition of the total generation depends more on the time of day (RES generation) than on the load level.

Comparing the total generation and the marginal mix shows that pumped storage power plants are over-represented in the marginal mix, especially during high load ranges. This over-representation also applies to hard coal and natural gas. In contrast, the share of nuclear power in the marginal mix (included in *Others*) is lower than in the total generation.

10.4.2. Forecast for Marginal Emission Factors

For the short-term load forecasts, the grid search resulted in 30 or 35 neurons in the hidden layer. The average out-of-sample MAPE is 3.83 % averaged over the whole forecast horizon. Table 10.5 compares the MAPE for the MLP and the naive benchmark models. For all forecast horizons, the MLP outperforms the naive benchmark models. With increasing forecast horizon, the performance of the MLP approaches the naive benchmark models.

Visual examination of the forecasting errors does not reveal any clear patterns.

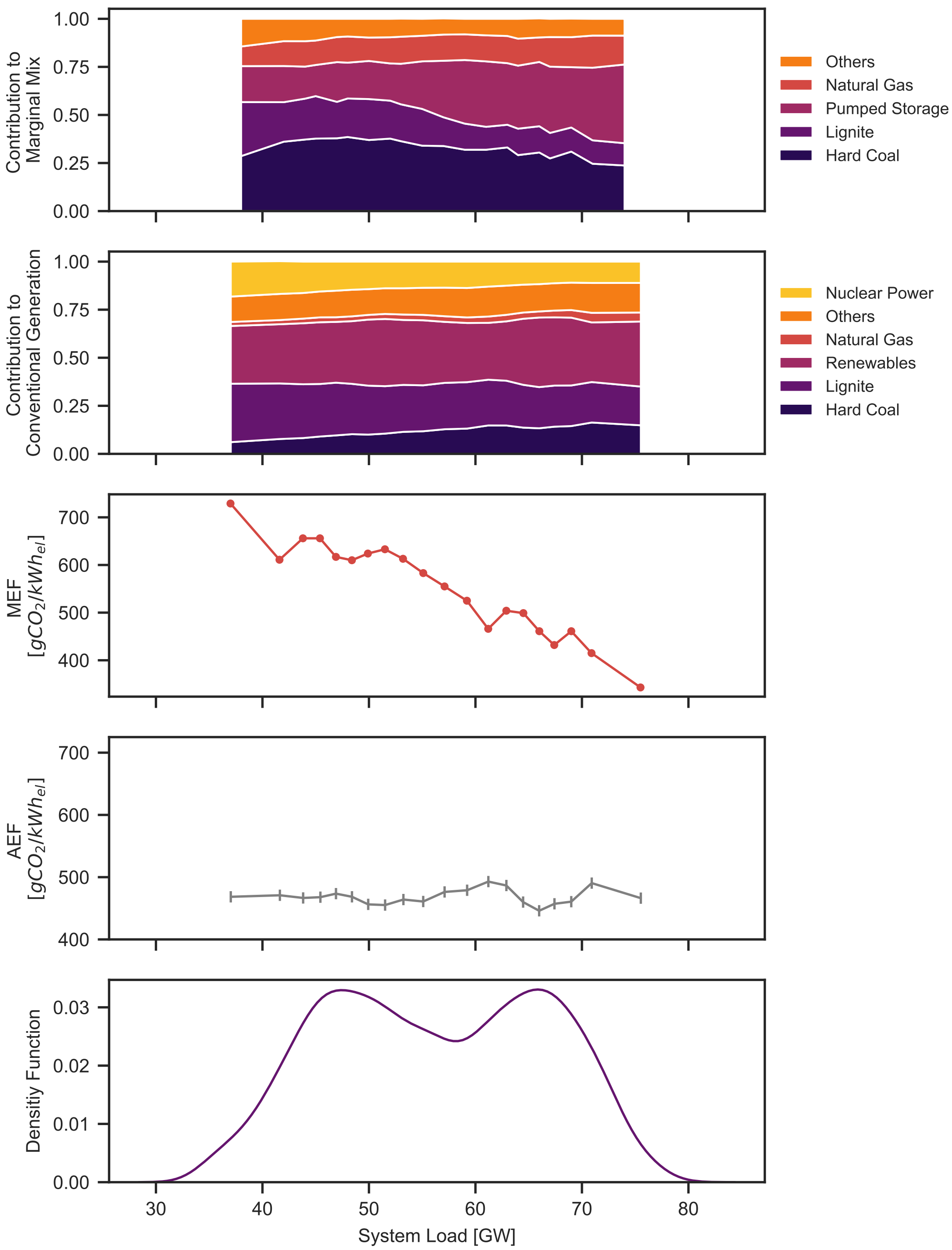


Figure 10.5.: In descending order: Share of generation technologies in marginal mix, share of generation technologies in total generation, marginal and AEFs, and density function of system load. All other graphs are in relation to system load. Style adopted from Thind et al. (2017).

However, the highest MAPEs (around 7 %) are at 6 a.m. and 7 a.m., while the average error decreases in the evening hours. The weekdays with the worst performance are Mondays and Saturdays. This error pattern indicates that the model did not learn to fully differentiate working days and weekends. The model put too much weight on the auto-regressive terms of the day before. This error could be reduced by training separate models for weekdays and weekends.

The forecasting errors for the MEF are lower as the emission factors are not forecasted directly, but are assigned to the forecast load values based on the quantiles. The MAPE for MEF on the test set is 3.23 %.

Table 10.5.: Out-of-sample MAPE in % of the load forecasters by forecasting horizon.

Horizon [h]	MLP	$\hat{y}_t = y_{t-168}$	$\hat{y}_{t_{[1,8]}} = t_0$
$t_0 + 1$	1.95	4.66	3.71
$t_0 + 2$	3.23	4.64	7.13
$t_0 + 3$	4.00	4.63	10.26
$t_0 + 4$	4.02	4.60	13.03
$t_0 + 5$	4.20	4.59	15.53
$t_0 + 6$	4.31	4.60	17.66
$t_0 + 7$	4.38	4.68	19.55
$t_0 + 8$	4.57	4.69	21.01

10.4.3. CO_2 Optimized Charging

Finally, we evaluate the CO_2 saving potentials based on analysis of the charging scenarios. We present the results in the order of the research questions.

CO_2 Saving Potentials of Smart Charging Comparing the emissions of dumb $\Psi^{u,MEF}$ and smart charging under prefect foresight with $\Psi^{s,MEF}$ allows to evaluate the full CO_2 saving potentials. Based on an assumed charging duration of three hours within a parking period of eight hours, the average CO_2 saving potentials are 7.43 %.

Figure 10.7 shows the average CO_2 saving potentials of $\Psi^{s,AEF}$ and $\Psi^{s,MEF}$ grouped by time of day. The most substantial saving potentials of over 10 % exist in the morning hours between 0 and 5 a.m.. Due to the lower system load in the morning hours, there are high MEFs (see Figure 10.5). With a high parking duration of eight hours, charging sessions could be shifted to the hours with lower MEFs after 6 a.m. During the load increase in the morning, there is a drop in MEFs resulting in the greatest saving potential. In contrast, there are only very small saving potentials of less than 2 % between 3 p.m. to 9 p.m.

The CO_2 saving potentials depend strongly on the selected charging parameters and the end-users time flexibility (i. e., parking duration). Figure 10.6 shows how the saving potentials depend on the parking duration (i. e., time flexibility) and the time of arrival. Adding one hour to the available charging time results in an average saving potential of 1.5 %. The highest emission savings of 24.0 % are achieved starting the charging session at 03:00 a.m. with high flexibility (i. e., a parking duration of eight hours when only three are required for charging).

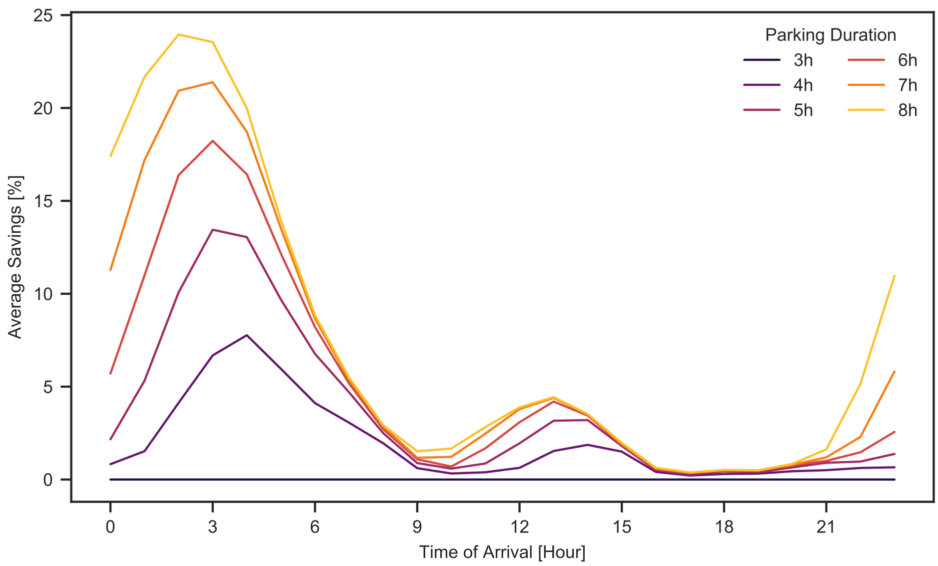


Figure 10.6.: Mean hourly CO_2 saving potential in relation to time of arrival and parking duration if three hours of charging were required.

Suitability of Average Emission Factors Next, we evaluate how well the saving potentials estimated with AEF do approximate the results using MEF by comparing the saving of $\Psi^{s,AEF}$ compared to $\Psi^{u,AEF}$ with the savings of $\Psi^{s,MEF}$ compared to $\Psi^{u,MEF}$.

The average savings potential with AEFs (i. e., $\Psi^{u,AEF}$ to $\Psi^{s,AEF}$) is 6.0 % and on the same level as the MEF. The potential is on the same level (6.40 %) as Huber and Weinhardt (2018) using the same assumptions and the same year.

Figure 10.7 compares the estimated average savings potentials in the optimization of MEFs and AEFs depending on the time of day at charging duration of three hours within a parking period of eight hours. Based on AEFs, the most substantial savings would be achieved when starting the charging period at 6 a.m.. The smallest saving potentials are at noon. The evaluation using MEFs results in a similar curve. However, the cure shows an offset in time with a higher maximum value at 3 a.m.. This offset results in different recommended actions for a CO_2 efficient charging. Using AEF instead of MEF underestimated the savings on average and can misinform the users on the best starting times for saving CO_2 emissions.

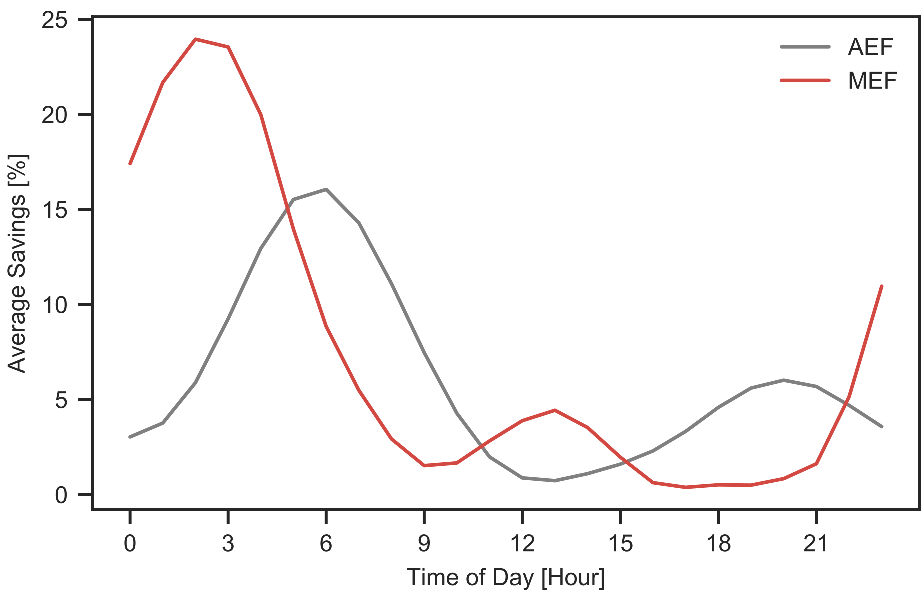


Figure 10.7.: Mean hourly CO_2 saving potentials based on average and marginal emission factors.

Potentials of a Real-Time Forecasting System Using the forecasted MEF in scenario $\hat{\Psi}^{s,MEF}$ compared to perfect foresight $\Psi^{u,MEF}$ for a eigth hour parking duration and three hours needed for charging only reduces the average saving potentials by 0.42 absolute percentage points from 7.27% down to 6.85 % on the test set.

The forecast can obtain CO_2 emission reduction in 85.6 % of occasions. However, the forecasting error can also shift loads away from low-emission hours and results in higher emission during charging. Figure 10.8 indicates that that there are 441 arrival times in the test set in which no emission savings are possible (i. e., the first three hours having the lowest emission factors). The forecast misses to realize most of the very high emission saving potentials above 20 %.

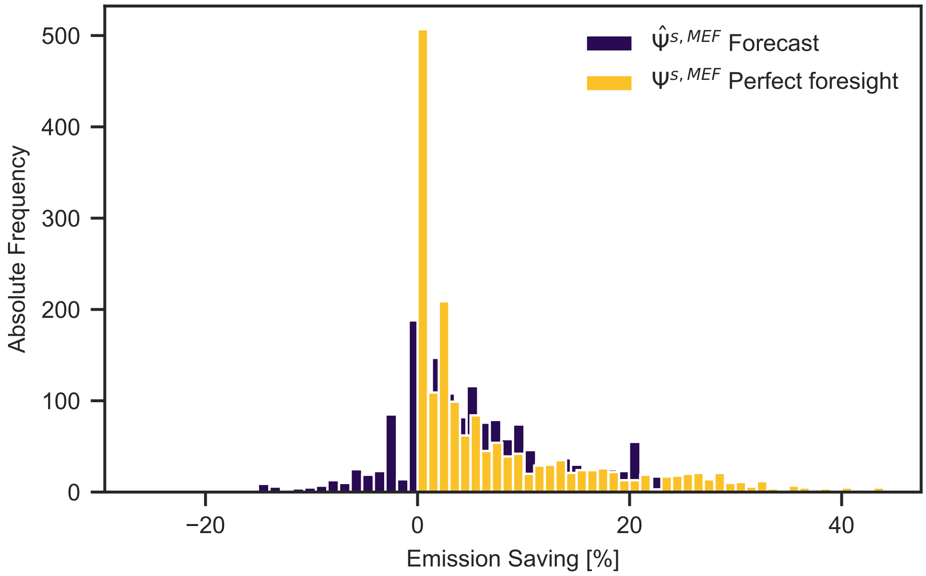


Figure 10.8.: Histogram of CO_2 savings on the test set with perfect foresight and forecasted marginal emission factors.

10.5. Discussion

As there is not directly observable ground truth data for MEFs, findings from this evaluation are sensitive to the assumptions outlined in the previous sections. Depending on the assumptions, evaluation could differ from other evaluations of the same year and energy system. We rely on the definition of marginal generation and regression model from Hawkes (2010) as this is well accepted in the area of research.

In this chapter, we calculate the MEF based on the marginal mix that includes the power plants that change their generation from one hour to the next hour. We decide against differing definitions in other studies. For instance, McCarthy and Yang (2010) base the MEFs on the marginal power plant (i. e., the last power plant that feeds into the grid to meet demand at a certain point in time). In their definition, the marginal mix contains all power plants that change their generation to meet the electricity demand of BEVs. Jochem et al. (2015) define the marginal generation as the amount of energy additionally required due to BEV charging in the long-term. We acknowledge that shifting a single BEVs charging load is unlikely to have any measurable influence on the composition of the marginal mix. However, using the definition and methodology of the marginal mix of Hawkes (2010) is more robust than estimating the single marginal power plant that changes generation in reaction to load shifting. Besides, shifting individual charging sessions would only cause small changes in consumption that will not have any effects in the merit order.

A limitation in the estimation due to data availability is that it considers only power plants with an installed capacity higher than 100 MW. Also, the estimation neither considers imports nor exports. As Germany generates 99.8 % of the annual electricity consumption itself, we assume that ignoring imports has limited effects (ENTSO-E, 2018). However, as 8.5 % of annual production is exported (ENTSO-E, 2018) this could have a substantial effect and provides room for further research.

As reported in the results, the forecaster for system load has weaknesses in differentiating weekends and weekdays. However, as the results of RQ 5 indicate, it is accurate enough to provide similar results as using the ground truth. However, we see a substantial number of 14.4 % events in the test set where using the forecast increases the carbon emissions, while the increase in these cases is rather low, such events could deter BEV users from using such systems.

Besides CO_2, we consider no other emissions (e. g., NO_x, particulate matter, or SO_x). First, these emissions are more unlikely to be motivating feedback to the end-user as Germany already meets its emission reduction target. Second, the negative health impacts of imissions of NO_x, particulate matter, and SO_x are mainly a problem in inner cities. As fossil power plant are mostly not in the city centre, the emissions caused by BEV charging are already less harmful than such of car with ICE in the cities.

Using input data in a one-hour resolution leads to the same resolution in all further analyses. When optimizing the charging sessions, shorter time steps would allow for a more differentiated consideration. As a a higher resolution would result in higher spreads in MEF, the analyses in this chapter are a conservative estimate for emission saving potentials, which could be even higher.

The analysis is agnostic to assumptions of BEV users' charging behaviour. Instead, we rely on the assumptions from Schuller et al. (2015) and Huber et al. (2019a) with a rather high charging power of 10 kW, compared to home charging, and an energy demand of 30 kWh. According to Schäuble et al. (2017) energy demand is often lower than 20 kWh and many charging sessions are rather slow, especially when charging at home. The methodology and data provided offers to compare different charging situations concerning their CO_2 saving potential. Such an analysis would help to put into perspective the high potentials at night that could be somewhat misleading. In reality, only a few BEVs would be connected at 3 a.m. and charged directly.

Last, the feedback system would propose shifting charging from low to high load levels. This advice might seem counter-intuitive to end-users and would send all users the same recommendation. If followed by many end-users, this advice could result in both higher energy cost (from operating expensive peak power plant) and grid congestion (due to the uniform signal for all users). As this is not a promising coordination signal, the proposed a feedback system seems to be more useful to communicate the benefits of smart charging in a single number (i. e., potential to avoid CO_2 emission) than as a system for actually scheduling smart charging.

10.6. Conclusion

In this chapter, we provide a real-feedback system and scheduling tool to avoid carbon emissions with smart charging. The system builds on three methodological aspects: the determination of MEFs for Germany based on Hawkes (2010), short-term forecasts of MEFs, and the calculation of the CO_2 optimized charging strategies. We hereby close the research gap to provide feedback for individual charging sessions based on MEFs.

As a byproduct, we calculated the MEF for Germany in 2017. The dataset is available at Lohmann et al. (2019). We find that the average MEF is $550\,gCO_2/\ kWh_{el}$ and is about 17 % higher than the system-wide AEF. In contrast to the AEF, the MEF show a strictly negative correlation with system load in Germany.

This negative correlation shifts loads towards times with already high loads. However, this would change with increasing CO_2 prices that would move CO_2 intensive power plants to the end of the merit order. The highest CO_2 saving potentials for smart charging are when the charging session would start at night (low load, high MEF) and is shifted towards morning (higher load, lower MEF).

Feedback based on AEFs (as done in Huber and Weinhardt (2018)) can provide end-user with false information and even result in a worsening of CO_2 emission. For example, an AEF-based system would propose charging around noon, while the real saving potentials are higher at night (Figure 10.7).

We find that forecasting the MEFs based on a simple short-term forecast of the system load allows building a real-time feedback system that only performs slightly worse than compared to perfect foresight.

BEV users are more motivated to use smart charging systems (Will and Schuller, 2016) and are more flexible in their charging setting (Huber et al., 2019a) if the systems consider environmental issues. The proposed methodology can be implemented by a choice architect to provide BEV users with real-time feedback on their charging flexibility and work as an incentive to charge more flexibly. It would be interesting to examine out how such feedback would influence the willingness of BEV users to charge more flexibly in real-world charging situations. In particular, different framings can be used to explain the avoided CO_2 emissions. For instance, such a feedback system could express emission savings in mass, volume, or distance traveled with an BEV or conventional car.

CHAPTER 11

PROBABILISTIC FORECASTS OF TIME AND ENERGY FLEXIBILITY

This chapter is based on joint work conducted by Julian Huber, David Dann, and Christof Weinhardt, published in *Applied Energy*, cited here as: Huber et al. (2020a).

The previous chapter described how smart charging allows integrating more RES into the energy system. Feedback on RES integration could even motivate BEV users to charge with more flexibility and enhance sustainability. However, the charging of BEVs also challenges the electricity grid for several reasons. First, the maximum charging power is very high compared to other household appliances. Second, charging multiple BEVs often has a high simultaneity. To overcome these challenges, charging station operators can apply smart charging. Smart charging adjusts the charging power of individual charging sessions by reducing or postponing them. In this way, charging station operators can exploit low prices on electricity markets (Huber and Weinhardt, 2018), provide system services (Staudt et al., 2018a).

Smart charging relies on flexibility in the charging demand. Charging demand is flexible if the BEV's parking duration at the charging station is longer than the time needed to fulfil the BEV's energy demand. Ludwig et al. (2017) introduce the difference between two types of flexibility for industrial demand-side management, i. e., energy and time flexibility. We transfer this idea to the charging session of BEVs: Energy flexibility is the difference between the minimum required SoC and a fully charged battery. For instance, if the BEV users are confident that their next trip's energy demand does not require a full SoC, they can provide energy flexibility by articulating that they do not require a full SoC at the end of the charging session. Time flexibility results from the difference in time required to reach the final SoC and the parking duration between arrival and departure at the station. Higher flexibility sets broader constraints to the optimization of the charging session. For instance, reducing charging power to reach the same final SoC over a more extended period allows flattening load peaks.

To apply smart charging, the charging station operator requires a definite valuation of the time and energy flexibility of each charging session. Otherwise, the operator who uses smart charging runs the risk to constrain BEV users' mobility by the time of departure because the SoC is not sufficient for the BEV users to reach their intended destination. To mitigate the risk of insufficient SoC, smart charging system operators mostly rely on the users' agreement to charge flexibly. Here, the users accept that they cannot charge the BEV immediately and continuously at full capacity until the BEV reaches its full SoC.

To do so, the users can communicate their flexibility by explicitly entering the desired SoC and planned time of departure for each charging session. Analysis of Lee et al. (2019) show hat BEV users often perform poorly when asked to provide estimates of desired SoC and planned time of departure. In particular, the authors find that the user input often represents a worse prediction than simple quantitative forecasts. Alternatively, the users can define profiles that fit their driving habits and can be adapted if necessary (Huber et al., 2019a). Setting these defaults is not a trivial task as drivers have to consider multiple requirements and objectives.

In particular, BEV users often have a limited understanding of the energy system and their mobility patterns Biresselioglu et al. (2018). While goal framing can hint users to the useful objectives of smart charging and increase flexibility (Chapter 9), limited understanding of their own mobility patterns could have negative effects on their flexibility. As individual overestimate the probability of rare events (Thaler and Sunstein, 2009), Huber et al. (2018e) argue that BEV users could overestimate how much energy they require and suffer from charging fright (i. e., having anxiety of not having enough SoC when using smart charging) which leads to low flexibility. To overcome such biases, smart charging systems could provide decision support (Flath et al., 2012). For instance, smart charging systems could provide forecasts on the required SoC and parking duration for each parking event to set reasonable defaults. Findings from Chapter 7 show that defaults are a powerful tool of choice architecture and influence user behaviour.

Such forecasts could assist charging station operators and BEV users in finding the right amount of flexibility by predicting the charging flexibility and ensure that the flexibility allowed by the system does not interfere with the users' mobility needs. In particular, flexibility can be predicted by using forecasts for the expected parking duration and energy requirement of the next trip.

Alternatively to the users setting their preferences, the charging station operator can use such forecasts to identify charging events with high flexibility to intervene (e. g., by interrupting charging for a short period) without the users noticing. The system must be designed conservatively so that the times it overestimates the parking duration or underestimates the energy requirement for the next trip are kept at a minimum. To make conservative estimates, the forecasts have to consider their uncertainty so that the charging system operator is confident not to control the inflexible charging events.

Various parties are positioning themselves as charging station operators to take financial advantage of the flexibility in electric mobility. Grid operators want to use the flexibility for system services and congestion management, home-owners aim to maximize their self-consumption, while utilities and public charging infrastructure operators want to benefit from temporal changes in electricity prices. Also, manufacturers of electric vehicles are pushing into the market of charging infrastructure and energy trading, e. g., by offering vehicle-to-home solutions (Weiller and Neely, 2014). Compared to the other players, the vehicle manufacturers have an important asset for determining charging flexibility: Global Positioning System (GPS) data of the vehicle provides them with location data. This location data may enable a better prediction of parking duration and energy requirements. At business level, the question arises how big the advantage of this data is and whether charging station operators should invest in the acquisition of this data or leave the field to the vehicle manufacturers who have access to this data.

While previous scholars analyse the mobility patterns of car users (Zumkeller et al., 2011) and flexibility potentials of different BEV user groups (Schuller et al., 2015), to the best of our knowledge there is no established forecaster that allows predicting the flexibility of individual BEV charging events. Furthermore, it is still unclear what kind of data is required to predict the time and energy flexibility of BEVs.

To address this striking research gap, this chapter describes the development of a quantile forecast for parking duration and upcoming trip distance. We base our analysis on a German data set of travel logs and follow the framework for forecast development provided by Hyndman and Athanasopoulos (2018) shown in Figure 11.1 (also see Chapter 6). First, we outline the requirement for forecasts as input for smart charging systems. Next, we generate features from the travel logs to resemble the information that is available to charging stations from historical parking events or tracing users' travel data with smartphone applications. Next, we discuss feature selection reduction and propose forecasters. Following, we select a model based on cross-validation performance and discuss the forecasting results on the test set. Finally, we show how charging station operators can profit from using quantile forecasts to solve congestion or provide flexibility on an ancillary market. In doing this, we answer the following research questions:

RQ 6 *To what extent does travel data improve the accuracy of probabilistic forecasts for parking duration and next trip distance of individual parking events?*

RQ 7 *What number of mobility impairments can be avoided using a smart charging strategy based on probabilistic forecasts as compared to point forecasts?*

We answer RQ 6 comparing the cross-validated performance of forecasters with and without location data. RQ 7 is answered by using the best forecast from the model selection step to schedule BEV charging loads from the test set using a greedy heuristic.

With this chapter, we contribute by deriving interpretable features that can assist charging station operators ans smart charging systems to forecast parking duration and trip distance to predict BEV charging flexibility. We use these features to propose four forecasters that are evaluated on an open data set and can serve as a benchmark for further model development. The evaluation of the forecast results shows that charging station operators should acquire location data to improve forecast accuracy and use probabilistic forecasters instead of point forecasts when using real-world scheduling problems.

Step	Problem Definition	Gathering Information	Preliminary (exploratory) Analysis	Choosing and fitting Models	Using and evaluating a Forecasting Model
Implementation	Scheduling in Smart Charging	Feature Generation from Travel Logs (Table 11.2)	Data Description and Selection of Forecasters (Section 11.2)	Model selection via cross-valdiation (Section 11.4)	Evaluation of forecast results on test-set and in case study (Section 11.5)

Figure 11.1.: Implementation of the basic steps of forecasting by Hyndman and Athanasopoulos (2018) in Chapter 11.

The structure of the chapter bases on the framework mentioned above: After providing the problem definition in the first section, we describe the related work on forecasting in BEV charging in Section 11.1. Next, we introduce the data and derive features used for the evaluation in Section 11.2. Section 11.3 describes the methodology, including the choosing and fitting of the forecasters. The forecast results are presented in Section 11.4. In Section 11.5, we present a case study to evaluate the improvements obtained by the forecasts. The chapter closes with Section 11.6, discussing the results and a conclusion and practical implications in Section 11.7.

11.1. Related Work

The increased number of BEVs is being accompanied by scientists working on how to meet the challenges of increasing energy demand and the high simultaneity of charging sessions. In Xin et al. (2010), the authors discuss what kind of forecasts are valuable to foster the integration of BEVs into the energy system and charging station planning and operation. They mention the forecast of electricity cost (i. e., electricity price and charging demand), occupation of charging stations, and the development of the electric vehicle population. Indeed, several authors (e. g., Schellenberg and Sullivan 2011, Plötz et al. 2014, and Gnann et al. 2015) try to predict the long-term development of BEV diffusion for different countries. Given that these are, by comparison, long-term forecast, covering years, such forecasts are difficult to evaluate with real-world observations. While these forecasts provide a valuable foundation for strategic planning, their contribution to the day-to-day operation of smart charging systems is limited.

On the contrary, Wi et al. (2013) describe a smart charging method for smart homes with PV systems. Their method relies on a time series model for the feed-in of the PV systems and they assume perfect foresight on the BEV charging. Similarly, Schuller et al. (2015) assume perfect foresight on the mobility data provided by the German Mobility Panel (Zumkeller et al., 2011) for scheduling charging to integrate fluctuating RES using a linear optimization model. Their analyses show that different user types, e. g., retirees and full-time workers, show different charging flexibility. Likewise, Sadeghianpourhamami et al. (2018) find three distinct behavioural clusters in 387,524 BEV charging sessions from the Netherlands. The behavioural clusters differ in the location and the flexibility of the charging situation. They identify parking to charge, e. g., on a long journey, charging near home, e. g., overnight, and charging near work.

The tables in Appendix F list work concerned with forecasting (Table F.1) and simulating (Table F.2) of short-term charging demand. While simulations do not try to predict real-world data, they aim to provide realistic scenarios for BEV charging behaviour. In contrast, the forecasts in the upper half are evaluated against out-of-sample data.

While most papers forecast charging demand of an aggregated BEV fleet, only a few (Bikcora et al. 2016, Ai et al. 2018) forecast demand or occupation of single charging stations or households. Most forecasts and simulations rely on conventional trip data (i. e., from cars with ICE), assuming that they share BEV users' mobility patterns. Only a few studies rely on rather small samples of BEV charging (Bikcora et al. 2016, Ai et al. 2018). Forecasters are different machine learning, time series (Amini et al., 2015) or rule-based models of the charging behaviour (Xing et al., 2019). Both the input features of simulations and forecasts of BEV charging rely mainly on historic charging and parking patterns. Driving patterns and SoC patterns are most often used in simulations, but not in forecasts. In contrast, some forecaster use weather (Arias and Bae, 2016) or calendar data (Xydas et al., 2013) as external variables.

As most forecasters predict the aggregated charging load of BEV fleets and simulation results are not evaluated compared to ground-truth data, the predictability of a single BEVs charging behaviour is still unclear. The analyses mostly build on conventional trip data or historic charging patterns, which provide only limited

Table 11.1.: Example of travel log data for two drivers.

	Driver	Mo 00:00	Mo 00:15	...	Su 23:30	Su 23:45
distance	1	0	0	...	20	7
location	1	home	home	...	driving	leisure
distance	2	5	0	...	0	0
location	2	shopping	shopping	...	home	home

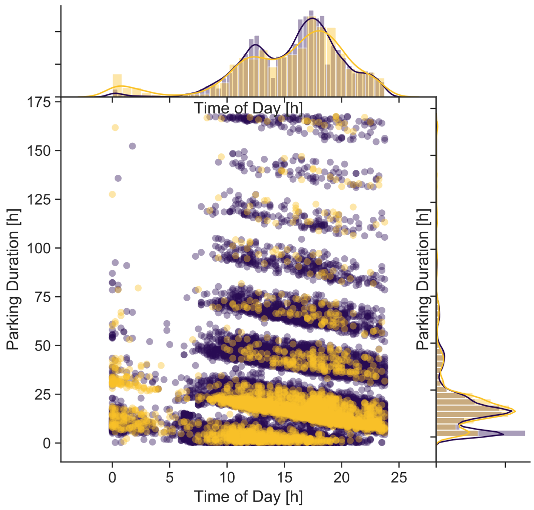
information about flexibility in the charging session. While many simulations consider spatial mobility patterns as an essential input, they seldom considered in the short-term forecast.

While there is no research on forecasting a single BEV's parking duration or trip distance and no insights on considering the uncertainty in such forecasts, there is a vast literature on probabilistic energy load and price forecasting (Hong and Fan, 2016). As the problem is relatively similar in terms of domain and time frame, in the following, we rely on findings and methods from this domain.

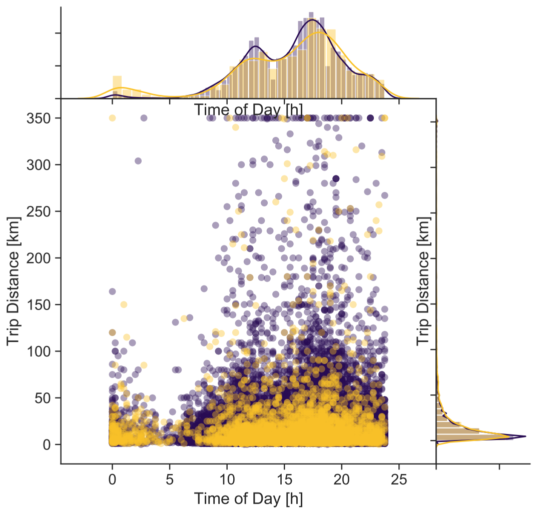
The review of existing literature shows that forecasting energy demands and parking duration of BEVs has not received enough attention. In particular, to our knowledge, there is no research on forecasting a single BEV's parking duration or trip distance as a proxy for its flexibility. Besides, there are no insights on considering the uncertainty in such forecasts as most prior work focuses on aggregated charging loads using point forecasts. This chapter provides charging station operators with novel insights regarding three aspects. First, we provide forecasts that allow assessing the flexibility of charging events compared to mere load forecasts. Second, probabilistic forecasts for individual parking events allow the account for their uncertainty. Third, we evaluate the importance of historical driving patterns as an input feature for such forecasters.

11.2. Data

Evaluating the impact of location features requires a data set of mobility patterns. We found only one publicly available data set containing trip trajectories in Xing et al. (2019). As this data stems from a ride-hailing company in China, it does not compare to residential BEV users charging at home. To the best of our knowledge,



(a) Parking duration in hours



(b) Trip distance in km

Figure 11.2.: Scatter plots for parking duration and trip distance at home in the data-set plotted by the time of arrival for working days (blue) and weekends (yellow)

there are no public data sets of BEV charging combined with location data of BEVs. For instance, Lee et al. (2019) recently published an extensive data set of charging sessions of public charging stations in the US. However, this data set does not provide information about the BEVs location data and, consequently, is not suited to answer the posed research questions. Hence, we use the data set provided by Zumkeller et al. (2011)[1] that is also used in the analysis of Schuller et al. (2015). The data set covers travel logs of 6,465 German car users.

The car users recorded their mobility behaviour for a whole week. The participants started logging their mobility patterns on different days. In the end, the data was aggregated starting on Monday. The time of data collection was selected so that there were no holidays during the recording period. During the week, the participants noted where they went, e. g., work, shopping, home, the mode of transportation, and the distance travelled by car. This data results in mobility diaries in 15 minutes resolution. Table 11.1 shows an extract of a travel log. User 1, for instance, is at home on Monday from 00:00 to 00:30. On Sunday 23:30 to 23:45, she drives 20 km, in the following 15 minutes, she drives for seven more km and arrives at a leisure activity.

As an input, we use these travel logs as time series data. We generate a new time series of parking events with entries at each arrival of a car at home. This time series contains different users. As the time series for each user is rather short (one week of data), learning weekly patterns to forecast the next week accurately is unlikely. However, we assume that users' mobility behaviour follows a weekly pattern. We use the whole data set of all users to train the model with information from all days of the week. The resulting time series contains all parking events in the data set with the IDs of the users and lagged features of the specific user (e. g., previous parking location).

While we cannot learn and forecast the weekly behaviour for a single user, we assume that there are similarities within the user types (as found by Schuller et al. 2015) from which the forecasters may learn. Consequently, we decide to derive aggregated features for single parking events, as described in the following. Another merit of this procedure is that the data sampling for training, validation, and testing is independent of the overall temporal order of the data. This split allows us to use

[1]available at `daten.clearingstelle-verkehr.de/192/`

cross-validation and an evaluation of the models' performance over the whole week (and not only the end of each week). For the cross-validation, we use data from the end of the week to train models that predict events that precede the training data. While some researchers propose rolling-origin evaluations, to simulate a realistic situation, where all the training data precedes the validation and test data (Tashman, 2000), Bergmeir and Benítez (2012) show that this has no adverse effect on the out-of-sample performance.

For further analyses, we make the following assumptions. We assume that the mobility patterns of conventional car users are the same for BEV users. Pasaoglu et al. (2014) analyse the potential of mobility surveys of conventional car owners to support studies on the impact of electric vehicles. They do not mention any differences in conventional car owners or BEV users. With insufficient BEV data available, most studies in Table F.1 use trip data from conventional cars. As most trips are rather short, 150 km range could cover 95 % of trips of German residential car users (Lunz and Sauer, 2015), we see no reason why BEV users would (have to) behave differently.

However, we cut off the longest trips at 350 km, which is the range of a current *Tesla Model 3* which is the best-selling BEV in US (see Table A.1). Apart from that, we apply no further cleansing as we see no unrealistic outliers. We next restructure the data, so that one observation represents a parking event, i. e., when a car is not used for driving. Note that a parking event is usually the moment when a BEV is parked and connected to the charging station. As most private BEV users charge their car at home (Hardman et al., 2018), we reduced the data to the parking events at home for the following evaluation. This reduction resulted in a total of 38,086 parking events at home. We further derived the set of features listed in Table 11.2 for all parking events.

For each parking event of index i, we make a forecast based on the data available on the start of the parking event at the time of arrival t^a being the forecast origin. Note that there are two variables of interest when scheduling the charging of a BEV by predicting its flexibility. First, the parking duration d_i determines the time flexibility by giving the time frame that is available for charging the BEV. The longer the BEV is parking at the charging station, the higher the time flexibility and opportunity for load shifting. Next, the user requires enough charge to reach the next charging station. The survey conducted by Huber et al. (2019a) shows that BEV users do not always require a full SoC after each charging session but are willing to provide flexibility in general. Hence, the charging session also has certain energy flexibility, i. e., the difference between 100% SoC and the SoC required for the next trip, which is highly correlated with the trip distance l_i of the next trip. Next, we aim to forecast trip distance and parking duration to improve the inputs for smart charging systems.

As mentioned above, different forecasters might have access to different amounts of data. The charging station operator knows the parking duration and energy requirements of the past charging sessions at the station for billing. For accounting, the operator will usually also have an identification of the BEV users, which enables the operator to learn from the driver's behaviour patterns. With one week of data, we only observe around five parking events per driver. As this is too short to learn distance patterns of a single user, we use the user type as an input feature. This feature set τ, available to the charging station operator, is denoted as $\tau_{station}$ in the following.

We define location features as information that requires knowledge on the BEVs' position over time, e. g., retrieved by GPS data. This information is available for vehicle manufacturer by on-board GPS or can be obtained by the charging station operator by tracking the BEV users via a smartphone application. As many people already share GPS data with application providers via their smartphone with little privacy concerns, we assume a charging station operator could obtain such data by its applications.

From the travel logs, we obtain the following location features: the last destination before arriving at the station (implemented as a category e. g., work, shopping, leisure), duration and distance of the last drive to the parking position, and the number, distance, and duration of previous trips of the same calendar day. The complete feature set, including location data, is denoted as τ_{all}.

In the way we derived features from the travel log, an arbitrary number of further features can be derived. We tested further features in pretests and evaluated them in terms of out-of-sample forecasting accuracy, but they did not improve models' performance significantly. Consequently, we remained with the features described in Table 11.2 as further features render understanding and interpreting the results more difficult.

Figure 11.2 presents the parking duration and trip distance for all parking events in the data set over a day. The histogram on the x-axis shows that most parking events at home occur either around noon or in the evening. Most parking durations (left graph) are rather short (below one day). Only a few parking events cluster around multiples of 24 hours, represented as the horizontal bands in the graph. These bands drop to the right, as cars that arrive later often still depart at similar times in the next morning. The trip distance in the right graph does not show such a distinctive characteristic. Most trips starting at home are rather short (below 50 km). With the same data set, Plötz et al. (2017) show that this distribution of trip length in Germany corresponds to a Weibull distribution. In so far, charging sessions with high flexibility (promising for smart charging) are the ones with high parking duration and short trip distances. The first group is in the upper segment of the left graph, where the time flexibility is high as only a portion of the parking duration is needed to charge the BEVs. The latter are the processes in the lower section of the right graph that have high energy flexibility as only little SoC is needed to fulfil the energy requirements of the upcoming trip.

Table 11.2.: List of predicted variables, indices, and input features.

Feature	Unit	Description	τ_{all}	$\tau_{station}$
i	1	index of the parking event		
t_i^a	time	start of the parking event		
Trip distance	km	length of the next trip following the starting event	$\hat{l}\|i, \tau_{all}$	$\hat{l}\|i, \tau_{station}$
Parking duration	min	duration of the parking event	$\hat{d}\|i, \tau_{all}$	$\hat{d}\|i, \tau_{station}$
Hour of arrival	{1, 24}	at start of the parking event	●	●
Weekday of arrival	{1, 7}	at start of the parking event	●	●
User	{1, 6465}	id of the user		
User type	{1, 6}	occupation of the user: full-time, half-time, retiree, education, homekeeper, unemployed	●	●
Previous parking location	{1,7}	last destination before arriving at home (work, home, shopping, service, leisure, vacation, business trip)	●	
Previous trip duration	min	duration of the last drive to the parking position	●	
Previous trip distance	km	distance covered by the last drive to the parking position	●	
# Previous trips	1	number of previous drives of the calendar day	●	
$\sum$ Previous trips duration	min	duration of all previous drives of the calendaric day	●	
$\sum$ Previous trips distance	km	distance covered by all previous drives of the calendaric day	●	

11.3. Methodology

Next, we develop promising forecasters to identity the most flexible charging sessions. As we find no benchmark models for this problem in literature, we decide to use forecasters used in probabilistic (electricity) load forecasting, which is, besides price forecasting, the most common forecasting task in the energy domain (Hong et al., 2016). In probabilistic forecasting, a forecaster (model) F does not aim to predict a single value $\hat{y}$, but the distribution of the forecasted value $\hat{P}(Y < y)$. Forecasters, hereby, often rely on a set of features τ that have some predictive power on the forecasted variable y.

$$F : \tau \rightarrow \hat{P}(Y < y). \tag{11.1}$$

In many cases, the forecasters do not predict a complete probability distribution $P(Y < y)$. Instead, they predict a selected set of quantiles Q (see Equation 6.3). In this way, many forecasters predict a set of quantiles Q to approximate the probability distribution $\hat{P}(Y < y)$. The quantile prediction allows accounting for the uncertainty in the forecast. Having information on the expected probability distribution is a valuable property in various use cases. For instance, they provide more information in decisions under uncertainty, as they provide information on the interval in which the realized outcome lies within a given probability. Especially for scheduling BEV charging, it is not only essential to know whether the starting time will be short or long, but also whether the forecaster is confident in its forecast. To derive a forecast for parking duration and trip distance, we follow the framework outlined in Figure 11.1:

After prepossessing (described in the previous section), we shuffled and split the data randomly in two parts. 85 % for training and model selection (training and validation set) and a 15 % hold-out sample for final evaluation (test set). For model, parameter, and feature selection, we perform five-fold cross-validation by splitting the 85 % training and validation set in five different folds. By choosing five-fold cross-validation, the validation sets have a similar proportion of the total data as the test set (17 % compared to 15 %).

To answer RQ 6 regarding the value of location information, we differentiate two feature sets noted in Table 11.2: A set τ_{all} that contains all features including location information and set $\tau_{station}$ that only includes data available at the charging station. We compare the cross-validation results for the forecaster with the smallest average difference in performance between two feature sets τ_{all} and $\tau_{station}$.

To substantiate the results of the model selection, we then evaluate the results on the hold-out test set. In contrast to measures for point forecasts e. g., Root Mean Squared Error (RMSE) or Mean Absolute Percentage Error (MAPE), pure accuracy measures for probabilistic forecasts are usually hard to interpret, as they do not provide an average or percentage deviation. Moreover, the framework of Hyndman and Athanasopoulos (2018) prescribes to use and test the forecasts in a use case. Following this framework, we apply the trained forecasters in a case study scheduling the interruption of BEVs' charging sessions. We use these results to answer RQ 6 on the value of probabilistic forecast in BEV scheduling problems. In the following section, we first describe error measures used as criteria for model selection. We then present the selected feature sets and forecasters.

11.3.1. Selected Features

Some of the features listed in Table 11.2 contain similar information. For instance, the previous trip duration and distance should show a high correlation. As some forecasters might perform better, when the set of input features is reduced, e. g., quantile regression (Guyon and Elisseeff, 2003), we consider performing a feature selection step for both forecasted variables. For both forecasted variables and feature sets ($\tau_{station}$ and τ_{all}), we perform a lasso regression (Ludwig et al., 2015) on the training and validation set. As the results of the lasso regression show non-zero coefficients for all features and forecasted variables, we decide to omit the feature reduction. The decision to do so is also motivated by the fact that the feature selection is based on a point forecast, while the final models aim at probability density forecast. A feature may have little information on the average parking duration or trip distance, i. e., not improving the point forecasts accuracy, but high information for predicting other segments of the probability density.

11.3.2. Error Measures

Point forecasts in energy forecasting are mostly evaluated in terms of RMSE or MAPE (Hippert et al., 2001). While the RMSE expresses the error in the unit of the forecasted variable, MAPE is a relative error measure that somewhat allows comparing the forecasters' performance on different data sets. The MAPE is given in Equation 6.9.

As Figure 11.2 shows, the distribution of data is very skewed in both parking duration and trip distance. To provide a error measure insensitive against very high observations, i. e., outliers being parking events with very the long parking duration and trip distance, we follow the recommendation by Armstrong and Collopy (1992) and also use the median of the absolute percentage errors (MdAPE):

$$MdAPE = median|\frac{\hat{y} - y}{y}| \cdot 100\%. \tag{11.2}$$

On the contrary, the evaluation of probabilistic forecast is less straight forward. Gneiting and Katzfuss (2014) and Gneiting and Raftery (2007) discuss prediction spaces, calibration, and sharpness as possible evaluation criteria and provide guidelines for proper scoring rules. Such scoring rules assign a numerical score $S(F, y)$ to the probabilistic forecast F and the observed value y. They propose the continuous ranked probability score and Dawid–Sebastiani score as a more practical alternative.

The energy load forecasting community establishes the pinball score a quasi-standard by using it in the evaluation of the global energy forecasting competition (Hong et al. 2016, Hong and Fan 2016). Accordingly, we decide to use the pinball score instead of the other available measures mentioned before. The pinball loss for each quantile q_a is calculated by

$$L_a(q_a, y) = \begin{cases} (1-a) \cdot (q_a - y), & \text{if } y < q_a \\ a \cdot (y - q_a), & \text{if } y \geq q_a. \end{cases} \tag{11.3}$$

This definition results in a tilted loss function resembling the trajectory of a pinball hitting the barrier having the following properties. If the observed value matches the predicted quantile, the loss function is zero for this quantile and non zero for all other quantiles. For the median (50 % quantile), the loss function becomes symmetric, returning half the absolute error. In case the observed value is higher than predicted quantile value, the pinball loss L_a returns a high penalty, especially for high quantiles.

We use the MAPE and MdAPE to evaluate the point forecasts being the prediction of the 50 % quantile. The pinball score is the average pinball loss L_a for all considered quantiles in Q. For the probabilistic forecasts, we use the pinball score for two reasons. First, it resembles the loss function in quantile regression, which is a forecaster often used to generate quantile predictions. Second, pinball score is well established and well understood in the energy forecasting domain, which makes it easier for fellow researchers to interpret and compare the results.

11.3.3. Selected Forecasters

In the following subsection, we describe the selected forecasters. These forecasters are based on models found in the energy forecasting literature, e. g., wind, solar, load, price. For each forecaster, we briefly describe the general idea and applications in energy forecasting. We further describe how we implement the forecaster for our evaluation.

Naive Benchmark

Forecasting often uses a simple (naive) model to evaluate the improvements achieved by the introduction of the more sophisticated models developed. For point forecasts of time series, a standard naive benchmark is to use the last observed value as a forecast for the next point in time (Hyndman and Athanasopoulos, 2018). Similarly, the mean observation in the training set can be used as a forecast. Analogously, we use the historical distribution, i. e., quantiles, in the training set as a forecast for the distribution for each observation in the test set. The histograms on the right in Figure 11.2 resemble these naive forecasters.

Quantile Regression

Koenker and Bassett (1978) introduced quantile regression in 1978. Quantile regression extends the ordinary least-squares estimation of conditional mean models to allow for the estimation of an ensemble of models for several conditional quantile functions. Since then it has become a standard tool for forecasting uncertainty in the energy domain (e. g., in Kaza 2010, Hammoudeh et al. 2014, Hong et al. 2016, or Liu et al. 2017). For our analysis, we use the implementation provided in Python package *statmodels* (Seabold and Perktold, 2010). In the following, we name the forecasters based on the model and the set of input features QR_τ (Quantile Regression), MLP_τ (Multi-Layer Perceptron), KDE_τ (Kernel Density Estimator), and $Naive$.

Quantile Regression with Multi-Layer Perceptron

The approach of quantile regression has been adapted by using similar loss functions within artificial neural networks to model non-linear relationships (Taylor 2000, Cannon 2011). Artificial neural networks with more conventional loss functions (e. g., absolute error) are a common forecaster in the load forecasting community (Hippert et al. 2001, He et al. 2016). In our analysis, we rely on the implementation provided by Abeywardana (2019). To answer RQ 6 on feature importance, we do not require the best forecast possible. Instead, we aim to find whether the additional features improve the forecast independent from the forecaster used. Consequently, we keep the neural network reasonably simple. We do not put much effort into the optimization of hyper-parameters, i. e., number of hidden nodes and layer, selection of activation function, and feature representation. As we use separate models for each quantile, the artificial neural network has a single output neuron predicting the quantile. We implement the neural network using Tensorflow (Abadi et al., 2016) and Keras (Chollet et al., 2015) by defining a tilted loss function that is the pinball loss $L(q_a, y)$ (defined above).

Based on a grid search in the cross-validation, the neural networks consist of two hidden layers with a number of units resembling the minimum of the number of input features or at least twenty. Such shallow networks are usually sufficient for comparable forecasting tasks (Park et al., 1991). We use a linear rectifier unit as an activation function (Li and Yuan, 2017):

$$f(x) = max(0, x). \tag{11.4}$$

The network is trained using the Adam algorithm (Kingma and Ba, 2014). To prevent over-fitting, training stops if the validation error does not improve for ten epochs.

Multivariate Conditional Kernel Density Estimator

On the contrary to quantile regression, Kernel Density Estimators (KDE) provide a full probability density (John and Langley, 1995). The estimated density function bases on the aggregation of kernels (often Gaussian distributions) based on historical data. An essential parameter in fitting such models is the bandwidth of the kernels influencing the smoothness of the fitted distribution. Conditional KDEs expand this concept to picture the conditional distribution given the realization of other continuous or discrete input variables. They have been used as a forecaster for smart meter data (Arora and Taylor, 2016) and wind power (Jeon and Taylor, 2012). We use the implementation provided by the Python package *statsmodels* (Seabold and Perktold, 2010). This package also includes a bandwidth selection heuristic (Bashtannyk and Hyndman, 2001) that we use in training the forecasters.

11.4. Forecasting Results

In this section, we first describe the results of the model selection step in the cross-validation and evaluate the value of local information answering RQ 6. We further check the results of the model selection step by presenting the results on the hold-out test set.

11.4.1. Cross-Validation

Figure 11.3 and Table 11.3 show the results of the five folds in the cross-validation. The dots in Figure 3 indicate the out-of-sample performance of the forecasters on different data splits. The out-of-sample performance results from the average pinball score of all predictions in the concerning hold-out sample. The hold-out sample is either one of the five validation sets from the cross-validation or the test set (see Section 11.3). For the parking duration, the MLP shows the best results on average. The QR also outperforms the naive benchmark for both feature sets. The KDE, however, does not achieve good results and performs worse than the naive benchmark. The variance in the pinball score of the $KDE_{\tau_{station}}$ with the smaller feature set is fairly high compared to the quantile regression models. For every single forecaster (QR, MLP, KDE), the forecast with the local information τ_{all}

outperforms the forecast using only station data $\tau_{station}$. Table 11.3 shows that pinball score is a good indicator of the MdAPE. Forecasters with a low pinball score also show a low MdAPE, around 30 % for the best forecasters. The MAPE, on the other hand, is very high (around 300 %). The high values are likely caused by the occurrence of high values in the distribution, i. e., the occurrence of very high parking durations, and cannot be clearly associated with the pinball score.

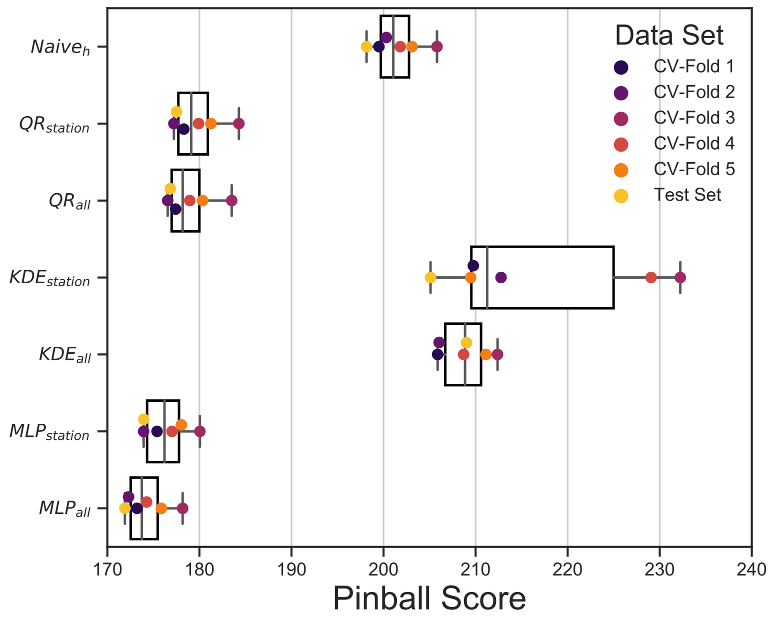
There is an underlying similarity in the pattern for the predictions of trip distance. On average, QR and KDE outperform the naive benchmark. However, the improvements of both QR forecasters and $MLP_{\tau_{station}}$ using only station data are very small. The $MLP_{\tau_{all}}$ with the full data set appears to be better on average than the other models. The model fitted and predicted the data very well on four of the five cross-validation folds (low bias). In contrast, it does not manage to predict the data well in the fifth fold (high variance). As the trip distance is limited to 350 km (i. e., maximum range and maximum charging requirement BEVs) in preprocessing, the distribution is less skewed (see Figure 11.2). As a result, MAPE (around 100 %) and MdAPE (around 60 %) are lower than those for trip distance.

11.4.2. Value of Location Information

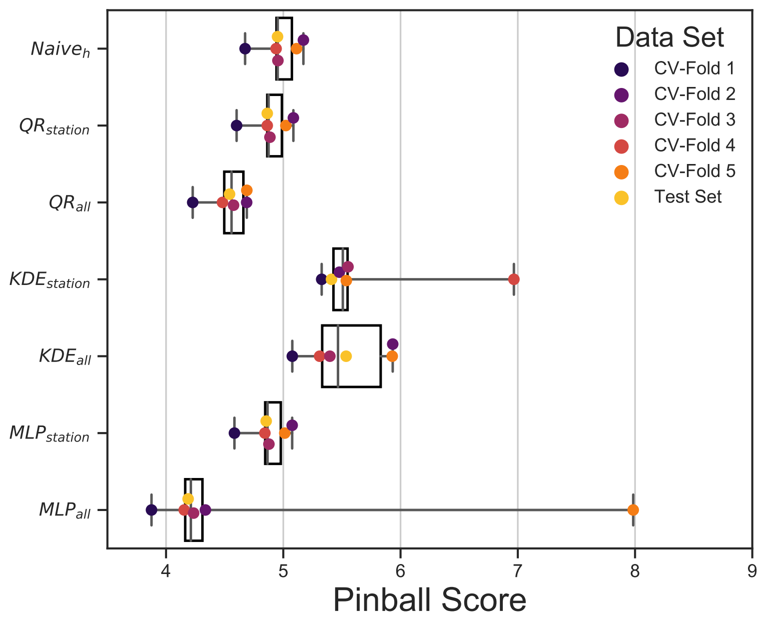
To answer RQ 6 on the value of location information, we investigate the forecaster (QR) as it is the most robust model and has the smallest difference in average pinball score between the full feature set τ_{all} containing local information and the reduced feature set $\tau_{station}$. We test the null hypothesis that there is no difference in forecasting accuracy, i. e., pinball score, between the same forecaster using the different feature sets:

$$H_0 : L_{QR_{\tau_{station}}} = L_{QR_{\tau_{all}}}. \tag{11.5}$$

As the pinball scores are not normally distributed, see Figure 11.3, and the samples are not independent, the data does not fulfil the assumptions for t-test or ANOVA. Consequently, we test the hypothesis using a Wilcoxon signed-rank test. This test requires paired samples, chosen at random, and a variable on an interval or ordinal scale. Wilcoxon test's requirements are met, as the cross-validation sets are created by shuffling the data. We compare the results of the same folds (one to five), and



(a) Parking duration



(b) Trip distance

Figure 11.3.: Cross-validation and test set performance of different forecasters evaluated using pinball score.

the pinball score provides an ordinal scale. For both, parking duration and trip distance, the test results in a test statistic of $V = 15$, rejecting the null hypothesis at a confidence level of $p > 0.03125$. Consequently, we answer RQ 6: The use of location data improves quantile predictions of both parking durations and trip distances.

11.4.3. Model Selection

On a practical level, the user of the forecast must decide what forecast to rely on an unseen data set. Typical criteria for model selection are the complexity of the learned classifier, generalization accuracy on new examples, and the amount of training data available and needed to achieve high accuracy (Engle and Brown, 1986). The amount of training data available is usually given ex-ante for each forecasting task and cannot be changed. Less complex models are often easier to interpret and less likely to overfit the training data (compare QR and MLP results for trip distance). High accuracy on an out-of-sample fit, e. g., using cross-validation, is usually the most important criterion in established literature (Hong et al. 2015, Hippert et al. 2001). This factor can be directly measured in the out-of-sample performance of the model. Often, the model selection is not based on statistical analysis but the rule of thumbs. For instance, (Hastie et al., 2009) chooses the model with the lowest complexity within one standard error of the best model, while Hong et al. (2015) test for the right weather station combinations to forecast electricity load and selects the set with the highest out-of-sample accuracy. Given the boxplots in Figure 11.3, $MLP_{\tau_{all}}$ reliably outperforms all other forecasters and should be selected. For trip distance, $MLP_{\tau_{all}}$ also has the lowest average pinball score. As the model shows poor performance on the fifth fold, we decide to use the second-best forecaster $QR_{\tau_{all}}$.

11.4.4. Model Performance on Test Set

The evaluation results on the test set in Figure 11.3 and Table 11.3 confirm the results of the cross-validation. For parking duration, the test set results are better than the average in the cross-validation for all forecasters but $KDE_{\tau_{all}}$. The selected model $MLP_{\tau_{all}}$ remains to be the model with the lowest pinball score. In the trip distance, there is a small worsening for the selected model $QR_{\tau_{all}}$. However, it remains the second-best performing model in the test set. The best model $MLP_{\tau_{all}}$

shows substantial improvement, as it is compared to the average of cross-validations (containing the outlier in the fifth fold). The MLP also seems to profit from the larger amount of training data resulting from the model being retrained on the set that was split in training and cross-validation before. On the test set, the relative improvement in pinball score achieved using the location data in $MLP_{\tau_{all}}$ compared to $MLP_{\tau_{station}}$ is 0.56 % for trip distance and 13.7 % for parking duration.

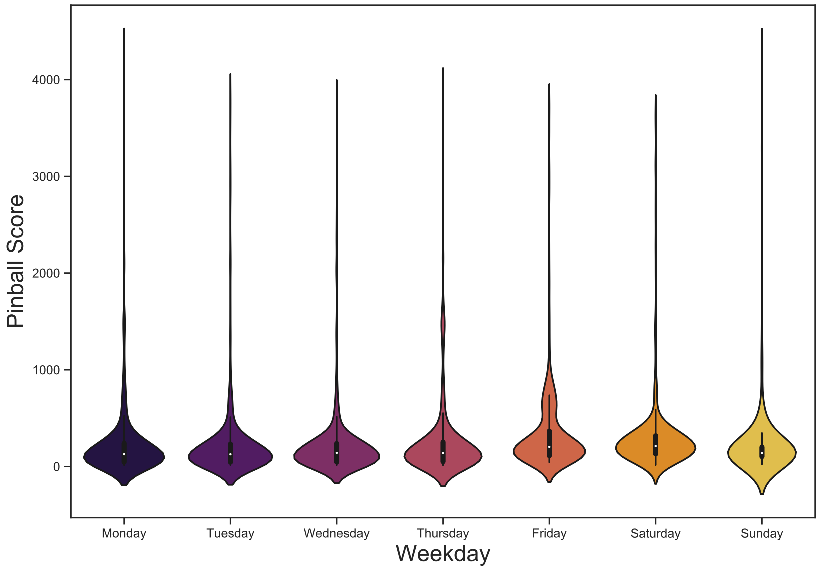
11.4.5. Error Analysis

Figures 11.4 a and b show the distribution of the pinball score for different days of the week predicted with OR_{all}. Each violin shows the kernel density estimation and box plot of the errors (i. e., pinball score) in the test set for different weekdays. For both parking duration and trip distance, the pinball score is rather low for most predictions. However, there are a few observations, where the prediction is very far off. There is no clear pattern for these outliers over the week. Predictions of parking duration (Figure 11.4 a) are, on average, worse on Fridays and Saturdays, showing a substantial number of poor predictions on Fridays. For trip distance (Figure 11.4 b), the highest variation in forecasting errors is on Sundays with no evident patterns in the average values over the week.

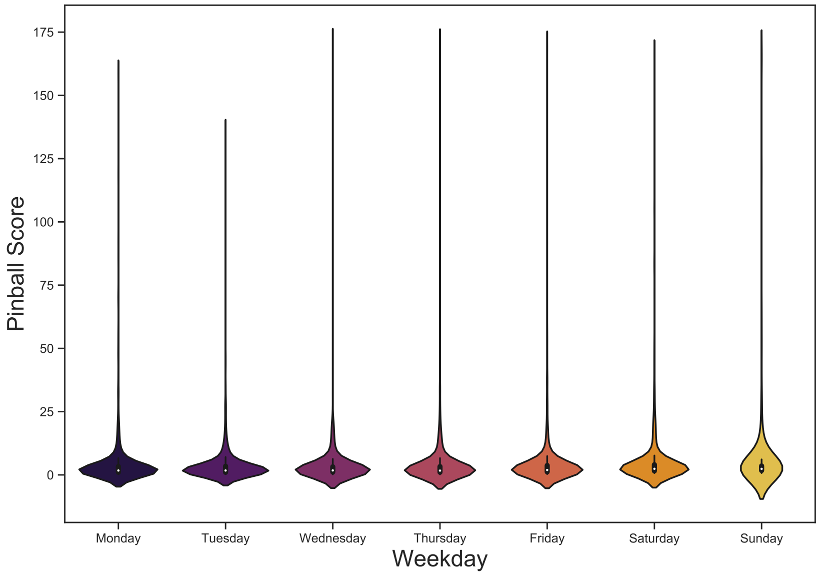
As we see no clear pattern for the outliers in the day of week and time of day, we look into the relationship between forecasting error and the observed values in Figures 11.5 a and b. The figures show the absolute percentage error (APE) in red and pinball score (grey) for all the observations in the test set. The APE compares the prediction of the 50 % quantile with the observed value, while the pinball score compares all predicted quantiles to the observation.

For both parking duration and trip distance, we see very high APE values when the observed variable assumes small values. The high error values are an artefact of the error measure: For instance, if trip distance or parking duration is very short (e. g., 15 min) and the prediction is close to the average parking duration around 500 min, this results in high APEs (for instance: (500 min-15 min)/15 min = 3,233 %). For higher observed values, the APE gets better for both trip distance and parking duration.

In contrast, we see an increase in pinball score with higher observations for both predicted variables. Here, the relative increase in pinball score is higher for parking durations (where the variance in the data is higher (see Figure 11.2).

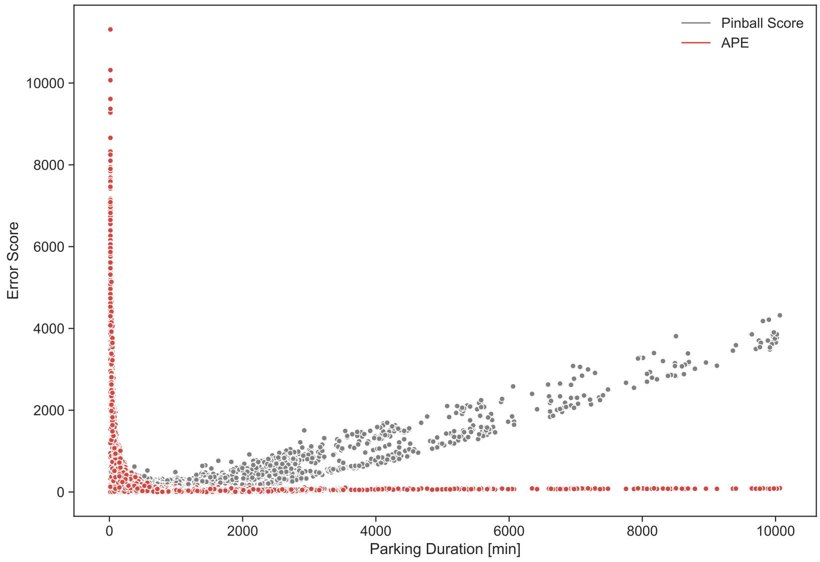


(a) Distribution of pinball score for parking duration for different days.

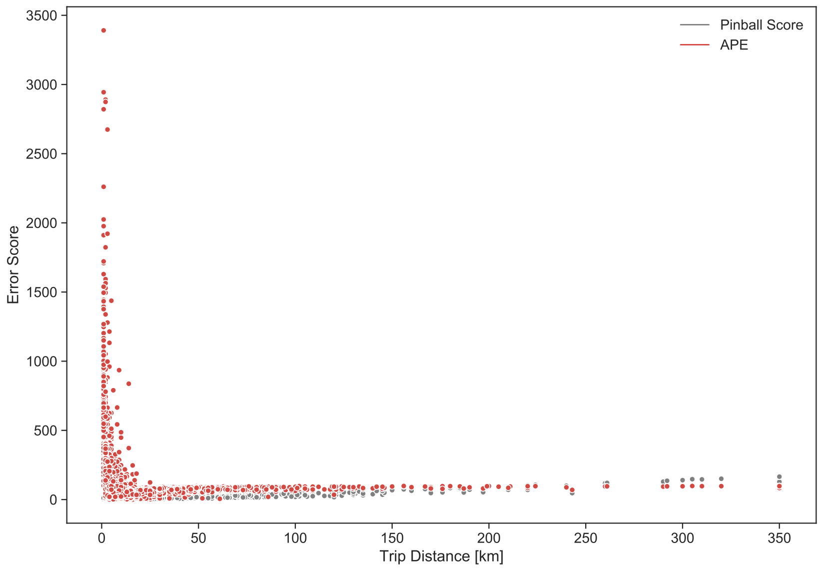


(b) Distribution of pinball score for trip distance for different days.

Figure 11.4.: Forecasting errors in the test set predicted with QR_{all} grouped by weekday.



(a) Pinball score and APE for parking duration in relation to observed values.



(b) Pinball score and APE for trip distance in relation to observed values.

Figure 11.5.: Forecasting errors in the test set predicted with QR_{all} compared to observed values.

Table 11.3.: Average cross-validation and test set performance of different forecasters.

Forecasted Variable	Model	Cross-Validation			Test Set		
		⌀ Pinball score	⌀MAPE [%]	⌀MdAPE [%]	Pinball score	MAPE [%]	MdAPE [%]
Parking Duration	$Naive$	202.10	381.05	40.15	198.15	394.22	40.54
	$QR_{\tau_{station}}$	180.20	302.85	32.14	177.52	302.36	32.29
	$QR_{\tau_{all}}$	179.35	301.97	32.13	176.84	302.49	31.91
	$MLP_{\tau_{station}}$	176.89	307.03	28.18	173.96	304.20	28.41
	$MLP_{\tau_{all}}$	**174.77**	295.18	30.55	**171.91**	299.37	29.83
	$KDE_{\tau_{station}}$	218.66	335.83	49.19	205.10	425.42	38.43
	$KDE_{\tau_{all}}$	208.82	375.18	40.89	209.01	511.73	42.56
Trip Distance	$Naive$	4.97	110.15	60.76	4.95	108.17	60.00
	$QR_{\tau_{station}}$	4.89	111.54	63.84	4.86	108.25	62.50
	$QR_{\tau_{all}}$	**4.53**	116.91	56.94	4.54	120.23	56.48
	$MLP_{\tau_{station}}$	4.88	110.37	62.54	4.85	110.29	63.10
	$MLP_{\tau_{all}}$	4.92	99.83	57.33	**4.19**	103.35	45.42
	$KDE_{\tau_{station}}$	5.77	190.51	100.38	5.41	137.50	66.67
	$KDE_{\tau_{all}}$	5.53	160.84	74.58	5.54	161.34	73.26

11.5. Case Study

For the case study, we assume that a charging station operator can control the charging of all BEVs in the test set. Figure 11.6 shows the aggregated number of assumed charging sessions in the test set. Most charging sessions at home start in the evening from Monday to Thursday. On Friday and Saturday, most charging sessions start around noon. The test set only contains a few charging sessions starting on Sunday. If no charging coordination is applied, the peak in numbers of charging sessions will likely lead to a peak in electricity consumption, which can cause grid congestion on distribution level (Salah et al., 2015). One way to avoid congestion is to interrupt some of the charging sessions in the BEV charging portfolio. For example, the German legislator proposes to register BEV charging stations as interruptible consumer facilities (EnWG § 19). For the distribution system operator (DSO) to interrupt them if necessary, the station operator benefits from reduced network charges. Other reasons for the operator to interrupt some of the charging sessions at point t could be to provide auxiliary services or the optimize against fluctuations in the energy markets.

In the case study, we assume that a charging system operator can control the charging of all the BEVs in the test set I. At each point t, in the test set, the charging station operators can decide to interrupt an arbitrary number n of the running uncontrolled charging sessions I_t. For each t and n, the operators have to decide for an order to interrupt the charging sessions based an interruption heuristic Λ. The set of the first n interrupted charging sessions at time t using Λ is $I_{t,n,\Lambda}$.

The BEVs are charged directly after arriving at home with the maximum charging power of 2.3 kW, i. e., a CEE 7/4 plug AC household socket charger outlet. To fulfil its driver's mobility needs, each BEV has to charge enough energy to last the next trip assuming an energy consumption of 20 kWh/100 km (United States Environmental Protection Agency and U.S. Department of Energy, 2016). All assumptions are laid out in Table 11.4.

This uncontrolled charging results in an uncontrolled charging period between the time of arrival t_i^a and t_i^b of parking event i:

$$t_i^b = t_i^a + \frac{\eta^{BEV} \cdot l_i}{\dot{C}}. \tag{11.6}$$

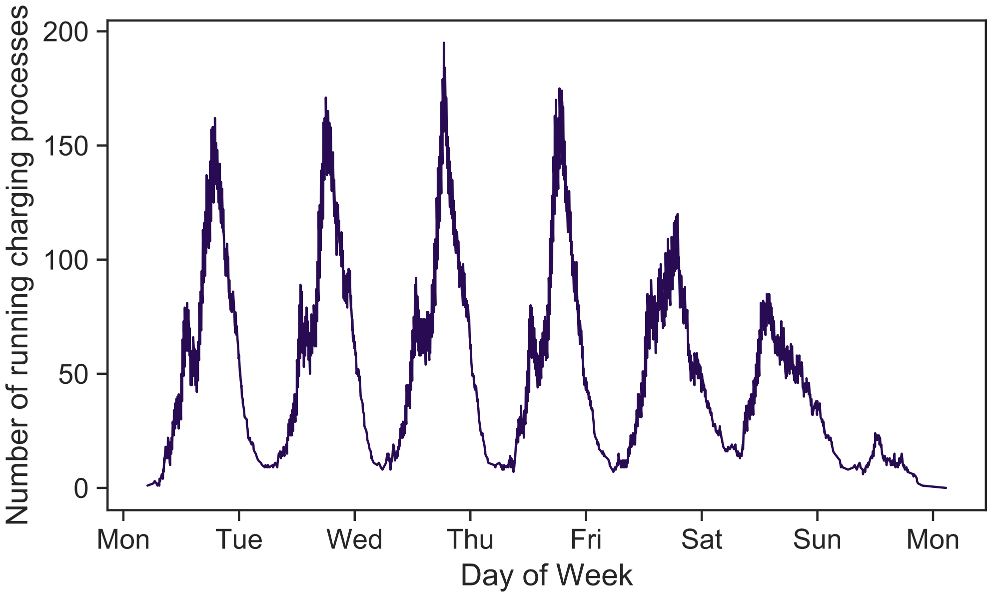


Figure 11.6.: Aggregated number of charging sessions (connected BEVs) at each time step in the test set.

Table 11.4.: Assumptions for charging infrastructure, interruption duration, and energy consumption in the case study.

Assumption		Unit
Energy consumption η^{BEV}	20	kWh/100 km
Maximum Charging Power $\dot{C}$	2.3	kW
Duration of interruption ι	60	min

11.5.1. Interruption Heuristic

Interruption strategies for BEV charging could follow on the intuition of time and energy flexibility: As long as parking duration is long enough to charge the BEV after the interruption, the interruption has no negative influence on the mobility of the BEV user. Not impairing the mobility is very likely for charging sessions with the following characteristics. If the next trip is rather short, the energy flexibility is high as only a small amount of energy has to be procured during parking duration. If the parking duration is long and time flexibility is high, there is enough time to charge even a substantial amount of energy. In contrast, interruptions leading to insufficient SoC at the departure impair the mobility of the driver.

Interrupting the charging sessions with the highest time or energy flexibility can be implemented by different heuristics. For instance, a first-in-first-out heuristic Λ_{FiFo} could start with interrupting the charging sessions of the BEV that arrived first.

In addition, the charging station operator can use the forecast for parking duration to estimate the quantile forecast of the time of departure t_i^d for each charging session:

$$\hat{t}_{i,q}^d = t_i^a + \hat{d}_{i,q}. \tag{11.7}$$

We derive the forecast for the parking duration $\hat{d}_i$ from MLP_{all}. The charging station operator can now apply $\Lambda_{\hat{t}}$ by interrupting the BEV with the highest remaining parking duration first. To account for energy flexibility, we also predict trip distance $\hat{l}_{i,q}$ using MLP_{all}. Using $\Lambda_{\hat{l}}$, the charging station operator starts with interrupting the charging sessions that are likely to be followed by a short trip and require little time for charging. As benchmark, we also evaluate interrupting the charging sessions by drawing at random Λ_{Random}.

The charging station operator applies a heuristic Λ, described in a scheduling Algorithm 1 to interrupt a given number n_t out of the currently running charging sessions I_t at point t in the test set. Algorithm 1 results in a list of interrupted charging sessions $I_{t,n}^{\Lambda}$.

Algorithm 1: Scheduling interruptions using heuristic Λ for interrupting n charging sessions in I_t

Data: I_t, n, Λ;
Result: $I_{t,n}^{\Lambda}$ list of interrupted charging sessions;
initialization;
sort I_t using interruption heuristic Λ;
set $I_{t,n}^{\Lambda}$ the first n charging sessions from I_t;
return $I_{t,n}^{\Lambda}$;

Each interruption in $I_{t,n}^{\Lambda}$ can result in an insufficient charge at departure if the duration of the interruption ι is so long that not enough SoC can be charged at capacity $\dot{C}$ to fulfil the next driving event of trip distance l_i at t_i^d in which case the mobility behaviour $\mu(i, \iota)$ of a charging session is impaired:

$$\mu(i,\iota) = \begin{cases} 1 & \text{if } (t_i^d - t_i^a - \iota)\cdot \dot{C} < l_i \cdot \eta^{BEV} \\ 0 & (t_i^d - t_i^a - \iota)\cdot \dot{C} \geq l_i \cdot \eta^{BEV} \end{cases}. \tag{11.8}$$

This formula assumes that BEVs arrive at the charging station with an SoC of zero and that the BEV can be charged at their next stop, so they do not get stranded there. While this assumption might is not realistic, it allows for a fair comparison between the heuristics as no other factors, i. e., SoC at arrival or location of the next stop, biasing the results.

This allows to count the number impaired mobility events z for interruption n charging sessions in t using Λ by:

$$z(t,n,\iota,\Lambda) = \sum_{i\in I_{t,n}^{\Lambda}} \mu(i,\iota). \tag{11.9}$$

11.5.2. Evaluation Scenario

We apply the interruption heuristics to 5,709 parking events in the test set. For each 15 min time slot t in C, we determine the number of running charging sessions I_t and count the number of impaired mobility events $z(t,n,\iota,\Lambda)$ when interrupting n charging sessions at t. For each time step, we apply all interruption heuristics Λ to interrupt one up to all running charging sessions. Note that for most time slots in the test set, several charging sessions cannot reach sufficient SoC even if uninterrupted.

To compare the performance of the different charging heuristics, we calculated the quotient Z of impaired mobility events. This quotient returns the share of charging events with insufficient SoC for all possible interruptions (i. e., interrupting one to all charging sessions for each point in time in the test set C):

$$Z(\Lambda) = \frac{1}{|C|}\sum_{t\in C}\frac{1}{n_t}\sum_{n\in I_t}\frac{z(t,n,\iota,\Lambda)}{n_t}. \tag{11.10}$$

11.5.3. Case Study Results

This equation results in the share of mobility impairment Z plotted in Figure 11.7. Drawing at random using Λ_{Random} impairs 25.1 % of mobility events. The first-in-

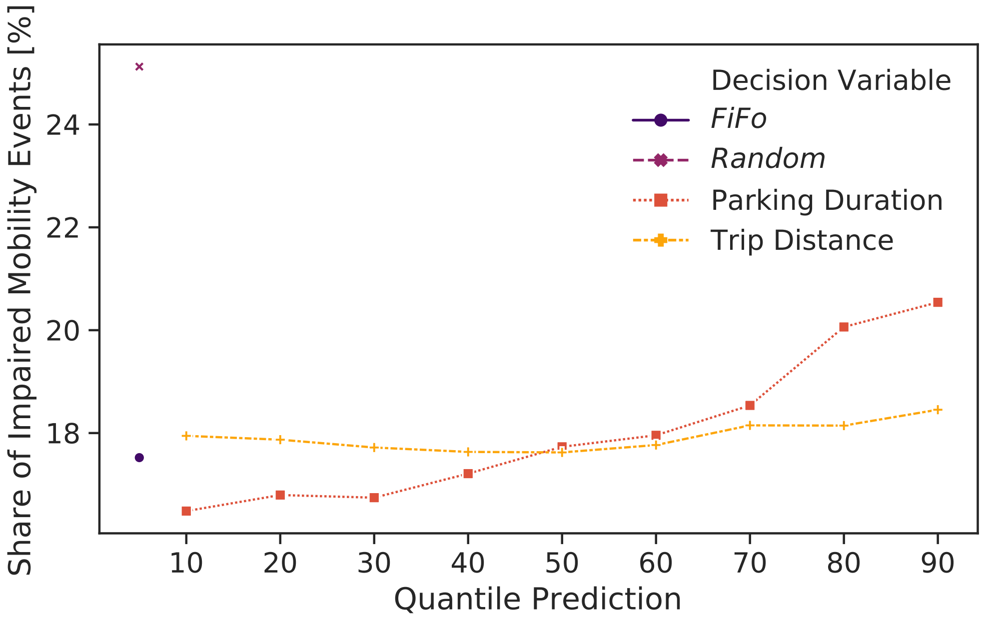


Figure 11.7.: Performance of interruption heuristics on the test set based on different decision variables.

first-out Λ_{FiFo} improves the share of impaired mobility events down to 17.5 %. Using the predicted trip distance as a heuristic $\Lambda_{\hat{l}}$ outperforms the random benchmark, but never outperforms Λ_{FiFo} no matter which quantile q is used.

There is a clear pattern in using $\Lambda_{\hat{t_d}}$. The prediction of the upper quantiles does not improve the scheduling of interruptions. Using the median prediction (50 % quantile) result in a higher interruption rate than the Λ_{FiFo} and $\Lambda_{\hat{l}}$. However, using the lower quantiles (10-30 %) improves the scheduling down to a 16.5 % interruption rate.

Using the 10 % quantile prediction Λ_{Q10} improves the rate of impaired mobility events to 16.5 %. The relative improvement of 7.0 % by using quantile predictions compared to point forecast answers RQ 7: Using probabilistic forecasts is beneficial in BEV charging coordination.

11.6. Discussion

This section starts with discussing the forecasts performance and error analysis. We next address the findings from the case study.

11.6.1. Forecasting Accuracy

All evaluated forecasters, except for conditional kernel density estimators, provide more accurate forecasting results compared to the naive benchmark. In this way, even charging station operators without location data may profit from the forecasters developed in this chapter. While the improvement of including location features is statistically significant, it is quite low. However, the difference might further increase with better data (e. g., trip trajectories).

However, even the limited location information in the data set can improve such forecasts. We assume that forecasts can be even more accurate if more data about the single users' behaviour is available. In this case, other forecasters like neural networks with long short-term memory could help to make use of this additional temporal information.

As discussed before, MAPE and MdAPE are sensitive towards low observation values in the data. The analysis of the pinball score indicates that the accuracy drops with high observations of parking durations. Such observations are very sparse in the data and probably not sufficiently considered in the model as the models stop at predicting the 90 % quantile. This results in around 10 % of observations that are higher than the predicted 90 % quantile. Some of them can be much larger than the predicted 90 % quantile resulting in a high pinball loss. This effect does not occur when predicting trip distance, where the distribution is less skewed. However, this is not a problem for most smart charging use cases where it is not crucial whether the parking duration is long or very long (e. g., one compared to several days of parking). In some use cases, it might be sufficient to predict a flexibility ranking of charging sessions compared to other running processes or are classification into different groups of short and long parking duration. In this way, all very long parking events could be grouped in one class (e. g., longer than one day) if the use case does not require information on how much longer the individual parking event is. In this way, the predicted variable would be less skewed and probably easier to predict. However, such classifications offer lower information content compared to quantile predictions.

The forecasting errors for both parking durations and trip distance are not particularly small in terms of MAPE and MdAPE. However, we could not find any similar evaluations to benchmark the results. Nevertheless, even if the forecasting accuracy seems low, the information derived from the probability forecast still helps with ranking the flexibility of different charging sessions.

11.6.2. Forecast Application

The application of the quantile forecasts in the case study shows that using forecasts for parking duration can improve scheduling of BEV charging. In this case study, the forecasts of the lower quantiles are more useful for this task than the point forecasts of the median values. However, the improvements are small compared to the first-in-first-out heuristic.

For interrupting the charging sessions with high flexibility, we use the low quantile value as a proxy for identifying charging events where we expect a long parking duration with high certainty. Quantile predictions lower than 10 % or other low quantile might work as well.

We keep the heuristic rather simple and do not consider the already achieved SoC at interruption time or a combination of the estimated time of departure and estimated trip distance. This simplification allows observing the benefits of probabilistic forecast without any overlays. Using forecasts for trip distance do not show a distinct improvement for different quantiles and are lower than the improvements for parking duration. Figure 11.2 shows that the distribution of trip distance is narrower than the distribution for parking durations (i. e., observed trip distances are closer together). We suspect that even with lower forecast errors, in general, this makes it harder to rank the charging sessions regarding energy flexibility. Besides, in the specific case study time, flexibility is more relevant than energy flexibility. If we observe a very long trip, it is more likely that its energy requirement cannot be fulfilled with or without the interruption. On the contrary, it is much more useful to differentiate the very short from the medium parking durations.

In case of congestion, a DSO might have to shed loads. In this case, the DSO has to decide which loads to shed. There are some non-discriminating options (reducing maximum charging power for all BEVs affecting the congestion or interruption in order of connection time, e. g., Λ_{FiFo} in the case study. However, the proposed forecasts for individual charging sessions provide additional information for this decision. In case a charging station operator interrupts the drivers charging session centrally, it seems unlikely that BEV users will accept smart charging schemes that impair their mobility even if it comes with a discount charging price. To overcome this challenge, the charging station operator might send out a notification to the BEVs drivers to approve the interruption in case of congestion. In this case, the charging station operator profits from an accurate forecast to decide which processes to interrupt and which BEV users to notify and ask to approve the interruptions. In this case, a more accurate forecast can improve the number of correct notifications, i. e., when the user accepts interruption and can increase acceptance of such smart charging schemes. Will and Schuller (2016) find that such personalized smart charging can increase acceptance of smart charging.

11.7. Conclusion

In this chapter, we describe forecasters for the time and energy flexibility of BEV charging that are needed for effective scheduling of BEV charging and can assist BEV users. We focus on charging at home and present how to derive a set of interpretable features from travel logs, charging stations, or GPS data that can be used to predict deciles of parking duration and trip distance as proxies for time and energy flexibility.

Our evaluation is based on an open data set from German drivers and shows that a multi-layer-perceptron with tilted loss function achieves the most accurate results compared to quantile regression, a conditional multivariate kernel density estimator, and a naive benchmark. In particular, we find that using location information of the BEV significantly increases the forecasting accuracy of decile forecasts evaluated in pinball score.

As the data set only provides limited data, i. e., one week, the forecasters cannot rely on long-term usage patterns of single BEV users. Given the limitations of the data set, we limited our efforts in feature engineering and hyper-parameter tuning. The proposed forecasters are rather simple to implement and can serve as a benchmark for similar forecasting tasks.

The findings demonstrate how charging station operators can build powerful forecaster with simple models and limited data. Besides, the results indicate that car manufacturers and other actors having access to location data have a competitive advantage in forecasting BEVs charging flexibility which may allow building business cases around this information advantage. Consequently, they will be capable of predicting charging flexibility more accurate. Location data provides them with an advantage in scheduling charging to optimize their energy procurement (Kristoffersen et al., 2011) or even tap into new revenue streams from balancing markets (Sarker et al., 2015). As using the location data has a significant benefit in predicting the distributions of parking duration and trip distance, charging station operators should aim to acquire such data, e. g., by using smartphones apps providing driver data or cooperating with car manufacturers. Otherwise, car manufacturers will have a competitive advantage in operating smart charging systems.

The findings are backed by the evaluation of a case study using a greedy heuristic for scheduling the interruption of BEV charging sessions. The heuristic is simple and only uses one out of nine deciles predicted in the forecast. The results show that charging system operators should not stick to simple point forecasts predicting the expected median or mean of the variables relevant for smart charging. Results show a 7.0 % relative improvement using the 90 % decile forecast compared to using conventional point forecasts.

Besides peak shaving, other use cases could profit from such forecasts. For instance, an aggregator using the flexibility from BEV to provide system services must know about the parking duration and energy demand of the BEVs to plan when he can provide how much flexibility.

In addition to helping charging station operators in scheduling decisions, the developed forecast can also be used as a choice architecture tool to aid the BEV users to decide when to charge in a flexible charging mode, e. g., when they have local generation powering their home charging station. Such feedback can help at integrating more local, RES in the mobility sector. Also, homeowners with PV generation and a home energy management system could profit from such forecasts. When the homeowners connect their BEV to the charging station, a local energy management system could generate a probabilistic forecast for the flexibility of the BEV. The forecast could also help end-users to overcome charging fright. Based on the risk preference of the BEV users, the energy management system could select a default charging settings that ensure a sufficiently charged BEV in 99 % of the historical cases. If BEV users know that their mobility behaviour does not correspond to this forecast, they could still overrule the forecasted default (compare Chapter 9). Integrating such a probability instead of point forecasts into the strategies of energy management systems or aggregators is another opportunity for further research.

When predicting the distribution in a higher resolution (more quantiles), the charging station operator could use this information for more detailed evaluations (e. g., selecting charging sessions by their probability of parking longer than an arbitrary time). Based on such considerations, a probabilistic forecast may constitute the basis for more sophisticated interruption and scheduling algorithms, that also include the actual SoC and expected trip distance.

Further forecasts besides parking duration and energy demand might be needed to improve BEV scheduling further. In particular, the charging operator could profit from forecasts on the occupancy of the charging stations before the BEV arrives at the charging station.

Based on such forecasts, more sophisticated smart charging methods, such as stochastic optimization, can be used to improve the scheduling of BEV charging. In this way, probabilistic forecasts of parking duration and trip distance will be a valuable tool for charging station operators and BEV users for integrating more BEVs in a grid friendly and cost-effective manner.

Part V.

Finale

CHAPTER 12

CONTRIBUTION AND IMPLICATIONS

BEV users can help to overcome the challenge to include a higher number of RES and BEVs into the electricity system if they accept smart charging. This dissertation contributes to solving this challenge by proposing UCSCS that consider the BEV users' needs and encourage them to provide flexibility during their charging sessions.

The engineering of UCSCS in this dissertation starts with understanding the requirements and objectives BEV users have during smart charging. Next, choice architecture and digital nudging provide ideas for increasing the charging flexibility of BEV users using interface design elements that address the requirements of the BEV users. Finally, this dissertation develops feedback, scheduling, and assistance functions for UCSCS based on energy analytics. In particular, this dissertation answers seven research questions (see Chapter 2) using online experiments and short-term forecasting.

Chapter 8 aims at understanding the requirements of UCSCS. The first research question is dedicated to identifying objectives that work from a technical perspective and are likely to persuade BEV users to use smart charging. There is still a limited number of BEV users who could be asked for their preferences in smart charging. Instead, RQ1 is answered using a literature review and a survey with domain experts and results in the following findings: While smart charging can address many optimization objectives, not all of them make sense from a technical perspective. For instance, experts see only small potential for slowing down battery ageing with smart charging, as the default charging modes already optimize battery lifetime. Smart charging allows to integrate a higher share of RES during charging, minimizing emissions of greenhouse gases and harmful air pollutants. Social aspects of BEV charging (e. g., who is allowed to charge in case of congestion) have gained little attention yet (see Chapter 5).

In summary, the expert-survey identifies cost advantages, congestion management and ancillary services, and the integration of RES as promising applications of smart charging as they rate high in technical accuracy. Out of these objectives, domain experts expect that cost advantages and RES integration are the most likely to convince BEV users to use smart charging. The design of UCSCS which consider the BEV users should focus on the objectives of RES integration and cost reduction to increase charging flexibility of BEV users.

Second, this dissertation addresses the question to what extent framing the charging decision towards these objectives can be used as a digital nudge to increase the flexibility of BEV users. Answering the second research question allows to validate the results of the first research question with actual BEV users. In particular, this dissertation describes a scenario-based online experiment (in Chapter 9). The results show that framing the charging decision towards different objectives can influence BEV users' charging flexibility. Monetary framing (i. e., mentioning potential cost savings without adding any monetary incentives) increases charging flexibility (i. e., users choose a lower buffer and final SoC) compared to a neutral framing. A framing message that highlights grid congestion and social aspects, in contrast, can even reduce charging flexibility. Environmental framing, on average, does not differ from neutral framings. However, many of the most flexible participants are found in the environmental framing group. This finding indicates that not all framing messages work to the same degree for all users. Hence, digital nudges could be more effective if they adapt to the particular user. In a broader perspective, the results show that it is worth considering the BEV users' willingness to provide flexibility not only from an economic perspective as only mentioning potential cost savings without giving an actual incentive can already significantly increase the BEV users' flexibility. Designers of smart charging systems should be aware that goal framing and other digital nudges will have an impact on how the users will interact with their systems.

As some BEV users are strongly motivated by integrating more RES generation during charging, the possibility to minimize CO_2 emissions during charging could be an incentive to charge with high flexibility. The third research question addresses the needs of such users and evaluates the potential CO_2 minimizing effects of smart charging. Evaluating the CO_2 emissions of charging flexibility allows UCSCS to provide BEV users with feedback on how much CO_2 they can avoid when charging more flexible. In analysing the emission factors of the German energy system in 2017, this dissertation finds that the highest reductions in CO_2 emissions during charging can be achieved if the BEV charging is shifted from morning towards noon. Given the mobility patterns of typical German end-users described in Chapter 5, smart charging at work would have the highest CO_2 minimizing potentials compared to other locations. Governments and employees should consider promoting charging stations at workplaces to increase the potential for CO_2 minimized BEV charging.

These results depend on the approach used to estimate CO_2 emission factors. There are two different approaches to calculate emission factors for the evaluation of CO_2 minimization potentials. Average emission factors that allow an attribution of CO_2 emissions are easy to compute and therefore used by many authors. To evaluate whether smart charging systems rely on this simple approach, the fourth research question evaluates to what extent average emission factors can approximate marginal emission factors. The analysis shows that average emission factors should not be used to approximate marginal emission factors as they would result in substantial miss-judgements in CO_2 emissions and minimization potentials during smart charging. Even worse, they could also recommend shifting charging towards hours that would even increase the CO_2 emissions of the charging session. These finding emphasize that evaluation of the effects of load shifting of smart charging and other demand-side measures on CO_2 emissions should always rely on marginal emission factors. In particular, the designers of smart charging systems could build on the data and methodology provided in this dissertation to make accurate calculations of CO_2 minimization potentials.

To achieve the CO_2 minimization potential found in the analysis above, smart charging systems require accurate forecasts of the marginal emission factors. This dissertation develops and evaluates a short-term forecast of marginal emission factors based on short-term load forecasts (RQ 5). The forecasting model for the marginal emission factors and corresponding data is published online and can be reused for other applications (Lohmann et al., 2019). A case study shows that this forecast is accurate enough to allow for substantial CO_2 minimization during charging sessions. Additionally, the developed methods allow choice architects to implement real-time feedback in smart charging systems. When the BEV users move the slider to select the temporal flexibility of their charging session, a UCSCS could offer instantaneous feedback on the expected CO_2 minimization potential of the charging settings. This feedback can provide a digital nudge to users who are motivated by the integration of RES during smart charging (see above).

While such feedback can nudge BEV users towards more flexibility, there are good reasons for the BEV users not to provide too much flexibility. For instance, if the flexibility in the charging setting is too large, the smart charging system might postpone charging so far that the BEV is not sufficiently charged should the BEV users return to their BEV for their next trip. UCSCS could provide decision support and assistance to determine the proper amount of flexibility. This proper amount of flexibility should balance between the BEV users' secondary objectives, e. g., CO_2 minimization, and their mobility needs.

This dissertation facilitates such assistance by developing a forecast for time and energy flexibility of individual charging sessions based on historical charging and mobility behaviour of individual BEV users. In particular, probabilistic forecasts of time and energy flexibility allow recommending an appropriate amount of charging flexibility to a given risk preference of the BEV users. The answer the sixth research question shows that BEV users can further improve the forecast actuary for time and energy flexibility if they are willing to share their location data of their BEV (e. g., GPS location from their smartphone) with the smart charging system. This finding reveals that additional data on the BEV users' mobility behaviour is a crucial asset to all charging station operators who wan to make a business model based on smart charging.

Last, such forecasts based on individual BEV users' data can also help actors on the supply-side in more efficient charging coordination. Given the current trends in German regulation where DSOs are encouraged to treat BEVs as interruptible loads (EnWG §14a), it seems likely that regulators themselves will establish flexible charging as the default to integrate a large number of BEVs into the electricity system. The DSOs could use forecasts of time and energy flexibility schedule interruptions in case of congestion. RQ 7 addresses such use cases and asks whether probabilistic forecasts of time and energy flexibility are more useful than point forecasts in BEV charging coordination. A case study shows that using these probabilistic forecast in scheduling interruption of BEV charging sessions with a greedy heuristic performs better than relying in point forecasts. Using probabilistic forecasts allows the charging station operator (e. g., DSO) to interrupt more charging sessions (e. g., using a higher amount of flexibility in case of congestion) without negatively affecting the mobility demand of the BEV users.

In this way, UCSCS consider the BEV users and the supply-side by fulfilling grid-centred objectives of DSOs, market-centred objectives of charging station operators, or locally centred objectives in a home energy management system. In each case, UCSCS components developed in this dissertation can help to increase charging flexibility to align the demand- and supply-side, making BEV charging more sustainable. The following paragraph provides an example of how the components developed in this dissertation can help to foster flexible charging as a convenient default in the everyday life of BEV users.

When setting up the system for the first time via a smartphone application, the BEV users are informed about the advantages of flexible charging in terms of cost reduction and RES integration. In the next step, the users can state their preferenced charging settings for different charging situations to set them as default. Influenced by the goal framing, the BEV users will probably choose more flexible defaults than in a neutral setting. Besides, the users can accept to share their smartphones' GPS location with the UCSCS. Based on this data, the smart charging system could forecast and recommend the individual users' charging flexibility for each particular charging situation based on their movements and charging patterns and improve the self-defined default settings. More, the users can enter a personal risk preference for the forecast-based charging settings. Based on the quantile forecast, the UCSCS could then set the flexibility in the charging settings so that the proposed flexibility level can ensure a high enough SoC to cover, an arbitrary number (e. g., 90 %) of all mobility requirements in a comparable situation. Likewise, users could adjust the defaults based on their personal preferences using other quantiles.

Once the BEV users connect their BEV to a charging station, the UCSCS can propose charging settings based on the forecasts and the BEV users risk preferences. The users could overwrite these proposals if they have additional information (e. g., if they plan a longer trip on the next day). While changing the charging settings, the BEV users obtain feedback on how this would influence the CO_2 emitted during the charging process. On most days, however, the users would not need to interact with the UCSCS as the proposed charging settings ensure sufficient SoC. In this way, intelligent defaults make flexible charging more convenient for the users and could establish smart charging as a norm.

The findings of this dissertation show how a user-centric perspective on smart charging system can help to integrate supply and demand-side. The results contribute to increasing the flexibility provided by BEVs to integrate a higher number of RES and BEVs into the electricity system.

CHAPTER 13

OUTLOOK AND RESEARCH OPPORTUNITIES

The findings of this dissertation show that choice architecture and digital nudging are promising approaches to change BEV users' behaviour towards smart charging. Besides framing, Chapter 7 lists a set of other possible digital nudges that could lead to more flexible charging. The effects of these nudges should be evaluated in further experiments to find the most effective way to increase flexibility in BEV charging. Testing these digital nudges in field-experiments would increase external validity compared to other settings. However, as the effect sizes of nudges might be smaller than the effects of goal framing in Chapter 9, such experiments would require a high number of BEV users using smart charging systems to generate significant results.

In particular, the feedback and decision support features developed in Part IV of this dissertation could be used in further digital nudges, that should be tested on their effectiveness on increasing BEV users' flexibility and technology acceptance.

Feedback about possible CO_2 minimization potential could be a way to convince users who are motivated by the integration of RES (see Chapter 9) to provide more flexibility. This dissertation used data from the German electricity market to estimate the CO_2 minimization achievable with smart charging.

If the energy for charging is not drawn only from the grid, but from a local RES of a building or in a local micro-grid the methodology should be expanded to address for the effects of the local generation. Estimating the CO_2 emissions in such a system would also require to forecast local generation and consumption which is likely to be more volatile that the emissions on system level. Depending on the generation structure this would result in higher saving potentials if the forecasts are accurate enough. To obtain real-time data as an input for the forecast, the local RES and the charging station must be connected into an internet of things. Given data connection and proofs of origin for renewable generation from RES, the concepts could also expand to connecting the charging station with a remote RES.

Regarding the user interface, the question arises to how the feedback on the avoided CO_2 emissions should best be expressed so that it is understandable and meaningful for the BEV users. While relative differences in CO_2 emissions expressed in percentage points or tons of CO_2 are very abstract, a digital nudge could translate this information into the CO_2 emissions of an traditional ICE car travelling a given distance or the CO_2 binding potential of trees. As end-users' understanding and acceptance is crucial to a successful energy transition (Mengelkamp et al., 2018), this mapping of the CO_2 emissions could be part of a larger discussion on how digital nudging could be a tool to increase end-users' understanding and acceptance of the changes during this transition.

As of 2020, there are only a few smart charging systems operating in the field and there is still much to learn about the BEV users' interactions with such systems. Huber et al. (2018e) discuss a model on how the objectives of the smart charging system, and user characteristics influence technology acceptance and flexibility provision. Based on an understanding of these relationships, choice architects could set out to design personalized nudges that fit the individual BEV user. Finding a large spread in the effect that environmental framing had on different BEV users shows that this might be a more promising approach than one-size-fits-all digital nudges.

Chapter 11 shows the power of machine learning using personal data for individual forecasts of charging flexibility. Artificial intelligence could not only learn the users' mobility behaviour but also what kind of nudging works for the particular user. Such self-learning digital nudging agents could become very powerful so that a discussion of ethical considerations and explainability of such systems becomes necessary.

Charging station operators could nudge BEV users towards high flexibility to earn money with this flexibility. The risk of choosing to charge too flexibly and having not enough SoC at the end of the charging session could be externalized to the BEV users. If nudges have a different effect on different users, some users could suffer an unfair disadvantage if they provide more flexibility without adequate compensations.

The consideration of fairness in BEV charging will become even more important as the number of BEVs rises and their charging will cause local congestion in the grid.

In such cases, local coordination mechanisms must be introduced to allocate the limited distribution grid capacity (Huber et al., 2018b). Local markets could use the willingness-to-pay of each BEV user to allocate charging capacity. However, as mobility is a basic need of human life, more complex matching markets could distribute charging capacity not only using financial metrics, but consider other factors such as mobility behaviour and socio-demographics. Another approach, not unlike nudging, could be to give communities the tools and platforms for self-administration of charging capacity so that they can allocate their limited capacity voluntarily. However, as the social framing in Chapter 9 shows a negative effect on flexibility, further research should explore what influences the effectiveness of normative framing. Follow-ups could investigate whether information systems can help to increase the sense of connection between BEV users within a community so that they are willing to provide flexibility for each other's mutual benefit.

A better understanding and forecasts of individual mobility behaviour is crucial for smart charging but also useful for other sustainable mobility solutions (e. g., car and ride sharing). Forecasts of mobility patterns not unlike the forecasts in Chapter 11 could also help with other mobility applications like optimized routing and fleet management for ride-hailing services. However, such improvement relies on the integration of high-resolution data of personalized mobility patterns (i. e., GPS-tracks). The first challenge is to derive valuable information from these large sets of spatio-temporal data. Here, machine learning could help to derive meaningful features, e. g., by learning when commuters are on their usual commute and when they deviate, so that their behaviour becomes less predictable. However, such data is very personal and sensitive. If users are not willing to share their mobility patterns with cloud services and still want to profit from its applications, analytics and coordination must become more decentralized. A promising approach is edge analytics, where the data is analysed at its origin (e. g., the users' smartphones). In this way, only the results must be transmitted to central coordinating entities. Edge analytics reduces the need for bandwidth and keeps sensitive data in the hand of the users. Continuing this path, information systems can contribute to coordinating supply and demand of energy and mobility more efficiently.

This dissertation outlined how UCSCS can integrate data for user assistance, education, and behaviour change towards more flexibility in BEV charging. In this way, UCSCS can encourage the individual BEV user to contribute to a more sustainable mobility and electricity system.

Appendices

APPENDIX A

SPECIFICATIONS OF BEST-SELLING BEV IN THE US (IN 2019)

Table A.1.: Specifications of best-selling BEV in the US (in 2019).

Model	**Battery Capacity [kWh]**	**Efficiency [kWh/100 km]**	**Price [$]**	**Type**	**Source**
Tesla Model 3 RWD	50.0	15.6	38,990	FEV	(Tesla, 2019a)
Toyota Prius Prime LE	9.0	15.8	27,600	PHEV	(Toyota, 2019)
Tesla Model X AWD 90D	90.0	20.7	84,990	FEV	(Tesla, 2019c)
Chevrolet Bolt EV	60.0	17.6	36,620	FEV	(Chevrolet, 2019a)
Tesla Model S AWD 100D	100.0	20.6	70,115	FEV	(Tesla, 2019b)
Honda Clarity PHEV	17.0	19.0	33,400	PHEV	(Honda, 2019)
Nissan LEAF (40 kWh)	40.0	18.7	29,990	FEV	(Nissan, 2019)
Ford Fusion Energi	7.0	20.5	34,595	PHEV	(Ford, 2019)
Chevrolet Volt	18.4	19.5	33,520	PHEV	(Chevrolet, 2019b)
BMW 530e	9.2	28.5	53,900	PHEV	(BMW, 2019)

APPENDIX B

OBJECTIVES AND INDICATOR KEYWORDS FOR SMART CHARGING

Table B.1.: Objectives and indicator keywords for smart charging.

Objectives	**Concept Indicators Keywords**	**Source**
Battery degradation	*lifetime, life-time, degradation, aging, cell*	(Schoch, 2016; Ortega-Vazquez, 2014; Sovacool et al., 2017)
Cost advantage	*market, markets, day-ahead, cost, aggregator, valley, price, prices, auction*	(US Energy Department, 2015; Brandt et al., 2017; Limmer and Dietrich, 2018; Li et al., 2018)
Social aspects	*social, fairness, community*	(De Groot et al., 2013; Koutitas, 2018; Limmer and Dietrich, 2018)
Integration of RESs	*pv, wind, renewable, RES, pollution, emission, emissions, solar, environment*	(Will and Schuller, 2016; Mwasilu et al., 2014; Huber and Weinhardt, 2018)
Congestion management	*load curve, flattening, peak demand, duck-curve, peak, congestion, bus, feeder*	(Mou et al., 2015)
Ancillary services	*frequency, voltage, power quality, loss, current, flow, reactive, security*	(Will and Schuller, 2016; Mojdehi and Ghosh, 2016; Mathur et al., 2018; García-Villalobos et al., 2014)

Table B.2.: Results of the literature review.

Source	**Objective**					
	Congestion Management	Ancillary Services	Battery Degregation	Energy Cost	RES Integration	Social Aspects
Deilami et al. (2011)		●		●		
Sortomme et al. (2011)		●				
Gan et al. (2013)	●					
	...					
	369	423	169	511	378	57

APPENDIX C

EVALUATION OF STATEMENTS AND GROUPED ACCEPTANCE FACTORS

Incentive	**Original Statements in German**	**Persuasiveness**	**Accuracy**
Cost advantage	*'Durch eine flexible Ladung kann der Nutzer von geringeren Strompreisen profitieren.'*	4.3	4.6
Cost advantage	*'Mit zusätzlich freigegebener Flexibilität kann günstiger geladen werden.'*	4.3	4.5
Integration of RES	*'Durch Ladeflexibilität kann der Anteil an erneuerbaren Energien zum Laden des Autos deutlich erhöht werden.'*	4.4	4.3
Cost advantage	*'Flexibles Laden kann Netzentgelte und Kosten reduzieren.'*	4.3	4.3
Environmental protection	*'Beim flexiblen Laden kann mehr Strom aus erneuerbaren Energiequellen genutzt und dadurch die Umwelt geschützt werden.'*	4.6	4.3
Cost advantage	*'Laden ohne zusätzliche Flexibilität kann mehr Geld kosten.'*	4.2	4.2

Integration of RES	*'Wenn Nutzer Ladeflexibilität bereitstellen, kann das Auto mit mehr Solarstrom und Windstrom geladen werden.'*	4.3	4.1
Social aspects	*'Das Stromnetz wird mit anderen Nutzern geteilt und profitiert davon, dass diese flexibel beim Aufladen von Elektroautos sind.'*	4.3	3.9
Environmental protection	*'Flexibles Laden ermöglicht die Vermeidung von fossilen Energieträgern und schädlichen Emissionen.'*	3.9	3.9
Integration of RES	*'Durch eine flexible Ladung können mehr erneuerbare Energien zum Ladeprozess genutzt werden.'*	4.5	3.9
Climate impact	*'Mit zusätzlicher zeitlicher Flexibilität kann man klima-schädliche Emissionen, die zum Klimawandel beitragen, einsparen.'*	3.9	3.9
Environmental protection	*'Je mehr Ladeflexibilität bereitgestellt wird, desto mehr klima-schädliche Emissionen können eingespart werden.'*	4.3	3.8
Environmental protection	*'Je flexibler die Ladung ist, desto besser können Ressourcen geschont werden.'*	4.5	3.8
Climate impact	*'Mit zusätzlichen zeitlichen Flexibilität kannst man einen positiven Beitrag zur Verminderung des Klimawandels leisten.'*	3.9	3.8
Environmental protection	*'Laden ohne Flexibilität strapaziert die Umwelt durch klima-schädliche Emissionen.'*	3.9	3.7
Environmental protection	*'Die Umwelt wird geschützt, wenn man Flexibilität beim Laden freigibt, da dadurch schädliche Emissionen eingespart werden können.'*	4.3	3.7
Grid impact	*'Flexibles Laden kann Netzengpässe und Netzaufbau vermeiden.'*	4.2	3.6

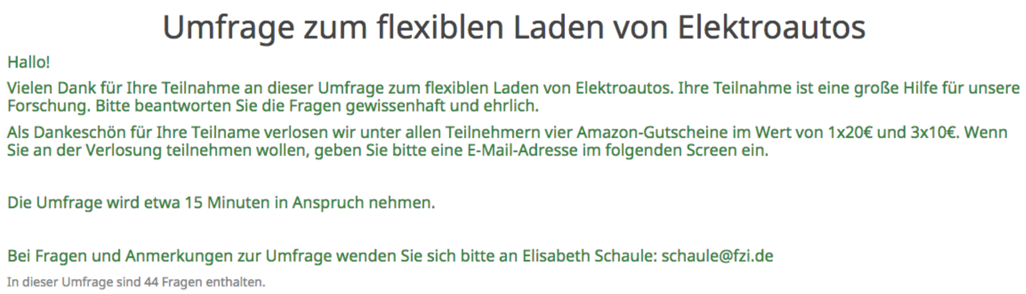
Grid impact	*'Laden ohne Ladeflexibilität kann die Auswirkungen auf Netz strapazieren und stellt eine größere Belastung für das Stromnetz dar.'*	4.4	3.5
Grid impact	*'Durch Flexibilität beim Laden wird das Stromnetz entlastet.'*	4.5	3.4
Grid impact	*'Eine flexible Ladung trägt positiv zur Auswirkungen auf Netz bei.'*	4.5	3.4
Grid impact	*'Durch Ladeflexibilität tragen die Nutzer zur Entlastung des Energienetzes bei.'*	4.2	3.4
Climate impact	*'Laden ohne Ladeflexibilität kann negativ zum Klimawandel beitragen.'*	3.8	3.4
Climate impact	*'Durch Laden zu Spitzenzeiten wird viel klimaschädliches Gas und Kohle verbrannt.'*	3.6	3.3
Battery degradation	*'Flexibles Laden kann zur Schonung des Akkus beitragen.'*	2.6	3.2
Social aspects	*'Elektroautonutzer sind sich einig, dass flexibel geladen werden sollte.'*	3.0	3.2
Health impact	*'Ladeflexibilität kann konventionelle Erzeugung vermeiden und somit gesundheitsgefährdende Emissionen einsparen.'*	3.9	3.2
Health impact	*'Keine oder geringe Ladeflexibilität kann zu höheren Emissionen bei der Energiegewinnung führen, die die Gesundheit belasten können (z.B. Asthma).'*	3.7	3.1
Health impact	*'Durch Laden zu Spitzenzeiten wird viel Gas und Kohle verbrannt. Luftschadstoffe aus konventioneller gewonnener Energie können zu Gesundheitsschäden führen (z.B. Asthma).'*	3.3	3.1
Battery degradation	*'Flexibilität bei der Ladung kann die Lebensdauer des Akkus erhöhen.'*	2.4	3.0

Social aspects	*'Andere Nutzer der Ladestation geben grundsätzlich während der Ladung Flexibilität frei.'*	2.8	2.8
Battery degradation	*'Laden ohne Flexibilität kann den Akku von Elektrofahrzeugen strapazieren.'*	2.3	2.6

Table C.1.: Statements with experts' evaluation average, ranked by persuasiveness towards end-users

APPENDIX D

LAYOUT OF THE ONLINE EXPERIMENT



Umfrage zum flexiblen Laden von Elektroautos

Hallo!

Vielen Dank für Ihre Teilnahme an dieser Umfrage zum flexiblen Laden von Elektroautos. Ihre Teilnahme ist eine große Hilfe für unsere Forschung. Bitte beantworten Sie die Fragen gewissenhaft und ehrlich.

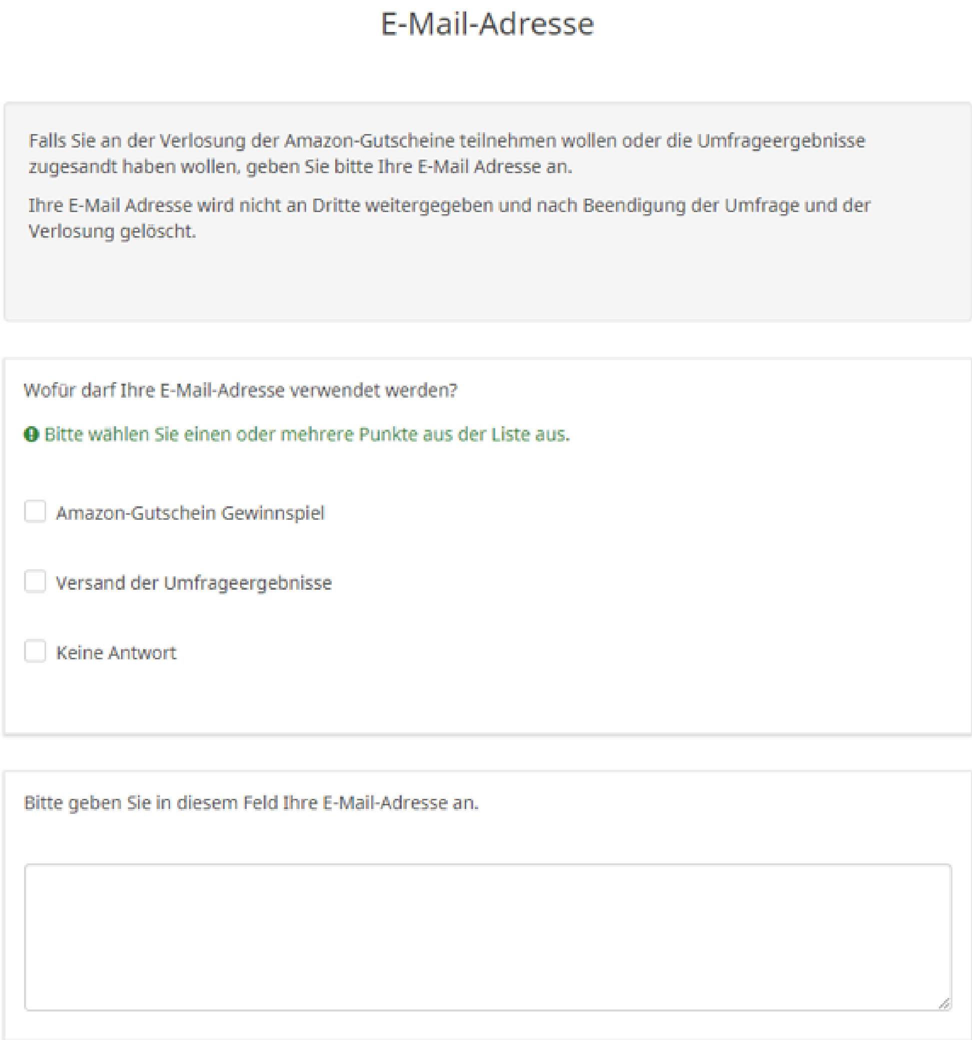
Als Dankeschön für Ihre Teilname verlosen wir unter allen Teilnehmern vier Amazon-Gutscheine im Wert von 1x20€ und 3x10€. Wenn Sie an der Verlosung teilnehmen wollen, geben Sie bitte eine E-Mail-Adresse im folgenden Screen ein.

Die Umfrage wird etwa 15 Minuten in Anspruch nehmen.

Bei Fragen und Anmerkungen zur Umfrage wenden Sie sich bitte an Elisabeth Schaule: schaule@fzi.de

In dieser Umfrage sind 44 Fragen enthalten.

Figure D.1.: Starting page of the experiment.



E-Mail-Adresse

Falls Sie an der Verlosung der Amazon-Gutscheine teilnehmen wollen oder die Umfrageergebnisse zugesandt haben wollen, geben Sie bitte Ihre E-Mail Adresse an.

Ihre E-Mail Adresse wird nicht an Dritte weitergegeben und nach Beendigung der Umfrage und der Verlosung gelöscht.

Wofür darf Ihre E-Mail-Adresse verwendet werden?

Bitte wählen Sie einen oder mehrere Punkte aus der Liste aus.

- Amazon-Gutschein Gewinnspiel
- Versand der Umfrageergebnisse
- Keine Antwort

Bitte geben Sie in diesem Feld Ihre E-Mail-Adresse an.

Figure D.2.: Question group *E-mail*.

Default für den Ladevorgang Zuhause

Stellen Sie sich vor, Sie haben ein Elektroauto mit einer maximalen Reichweite von 350 km und können es an allen Ladestationen (Zuhause, am Arbeitsplatz und unterwegs) zu gleichen Konditionen aufladen und nach Wunsch von Ihrem Smartphone aus den Ladevorgang zu jeder Zeit anpassen.

Sie haben sich soeben bei einem Anbieter für das Lademanagement ihres Fahrzeugs registriert und können nun anhand von einigen beispielhaften Ladesituationen Ihre zukünftigen Ladevorgänge konfigurieren. Diese Einstellungen wird das System im Zukunft standardmäßig vorschlagen, können aber jederzeit von ihrem Smartphone aus angepasst werden.

Nehmen Sie dazu an, dass der beschriebene Tagesverlauf Ihrem Alltag entspricht und machten Sie sich mit der App vertraut. Wählen Sie dann Ihre gewünschten Standardeinstellungen aus. Diese Standardladeeinstellung beruht auf zwei Werten:

- **"Mindestreichweite sofort":** Die Reichweite, auf die Ihr Elektroauto direkt ohne Unterbrechungen geladen wird. Ihr Elektroauto wird dabei mit der maximal möglichen Ladeleistung von 70 km Reichweite pro Stunde aufgeladen.
- **"Mindestreichweite später":** Die Reichweite, die Ihr Elektroauto mindestens bis zum nächsten Gebrauch haben soll. Ihr Elektroauto wird dabei in einem flexiblen Modus geladen, d.h. der Ladevorgang kann kurzzeitig unterbrochen werden.

Sie kommen nach der Arbeit gegen 18 Uhr nach Hause mit einem Ladestand von 30%, was einer Reichweite von ca. 105 km entspricht. Sie können nun ihr Auto zuhause laden, bis Sie es das nächste Mal morgen früh um 7:30 Uhr brauchen, um in die Arbeit zu fahren. Ihre Pendelstrecke (one-way) beträgt 75 km.

Bitte stellen Sie Ihre Ladeeinstellungen ein.

Figure D.3.: Question group *Home charging scenario (control group)* I.

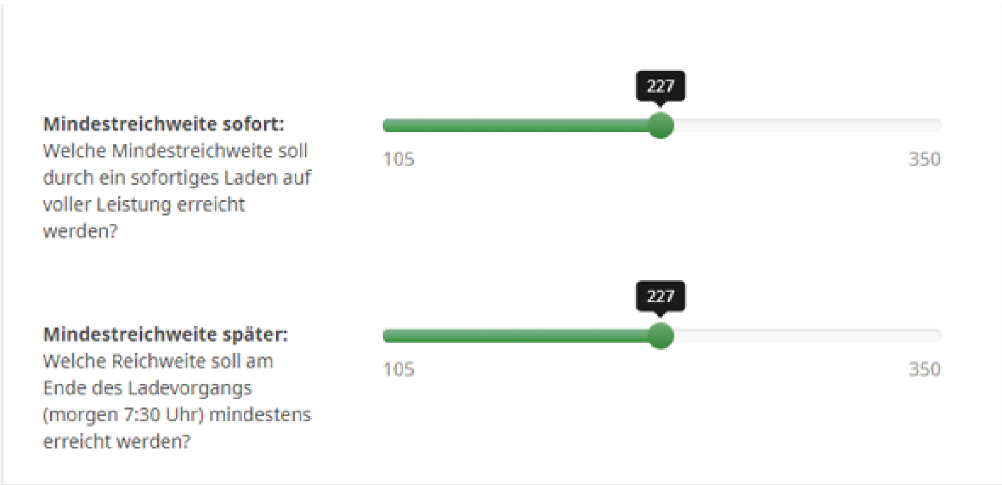


Figure D.4.: Question group *Home charging scenario (control group)* II.

Default für den Ladevorgang bei der Arbeit

Stellen Sie sich vor, Sie haben ein Elektroauto mit einer maximalen Reichweite von 350 km und können es an allen Ladestationen (Zuhause, am Arbeitsplatz und unterwegs) zu gleichen Konditionen aufladen und nach Wunsch von Ihrem Smartphone aus den Ladevorgang zu jeder Zeit anpassen.

Sie haben sich soeben bei einem Anbieter für das Lademanagement ihres Fahrzeugs registriert und können nun anhand von einigen beispielhaften Ladesituationen Ihre zukünftigen Ladevorgänge konfigurieren. Diese Einstellungen wird das System im Zukunft standardmäßig vorschlagen, können aber jederzeit von ihrem Smartphone aus angepasst werden.

Nehmen Sie dazu an, dass der beschriebene Tagesverlauf Ihrem Alltag entspricht und machten Sie sich mit der App vertraut. Wählen Sie dann Ihre gewünschten Standardeinstellungen aus. Diese Standardladeeinstellung beruht auf zwei Werten:

- **"Mindestreichweite sofort":** Die Reichweite, auf die Ihr Elektroauto direkt ohne Unterbrechungen geladen wird. Ihr Elektroauto wird dabei mit der maximal möglichen Ladeleistung von 70 km Reichweite pro Stunde aufgeladen.
- **"Mindestreichweite später":** Die Reichweite, die Ihr Elektroauto mindestens bis zum nächsten Gebrauch haben soll. Ihr Elektroauto wird dabei in einem flexiblen Modus geladen, d.h. der Ladevorgang kann kurzzeitig unterbrochen werden.

Sie kommen bei der Arbeit gegen 8:30 Uhr an. Der aktuelle Ladestand beträgt 9%, was einer Reichweite von ca. 30 km entspricht. Sie können Ihr Elektroauto laden bis Sie es gegen 17:30 Uhr für Ihren Heimweg (75 km) nutzen.

Bitte stellen Sie Ihre Ladeeinstellungen ein.

Figure D.5.: Question group *Work charging scenario (control group)* I.

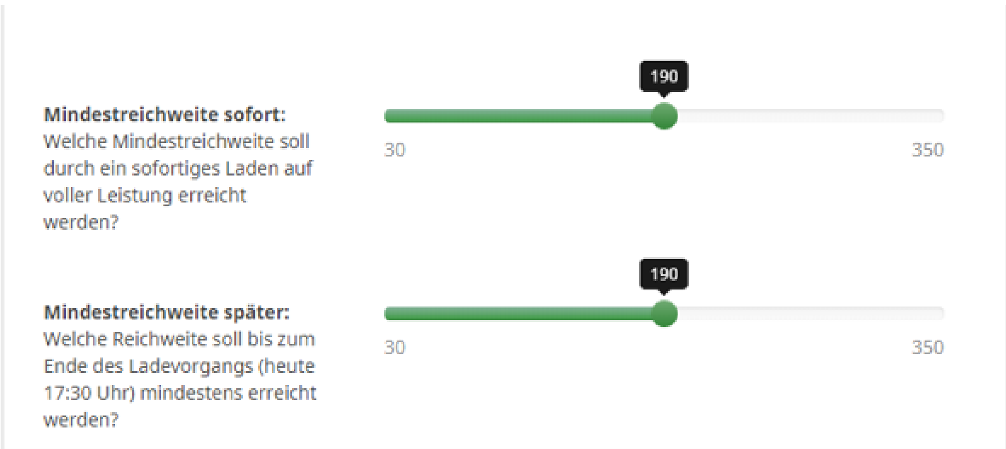


Figure D.6.: Question group *Work charging scenario (control group)* II.

Default für den Ladevorgang Unterwegs

Stellen Sie sich vor, Sie haben ein Elektroauto mit einer maximalen Reichweite von 350 km und können es an allen Ladestationen (Zuhause, am Arbeitsplatz und unterwegs) zu gleichen Konditionen aufladen und nach Wunsch von Ihrem Smartphone aus den Ladevorgang zu jeder Zeit anpassen.

Sie haben sich soeben bei einem Anbieter für das Lademanagement ihres Fahrzeugs registriert und können nun anhand von einigen beispielhaften Ladesituationen Ihre zukünftigen Ladevorgänge konfigurieren. Diese Einstellungen wird das System im Zukunft standardmäßig vorschlagen, können aber jederzeit von ihrem Smartphone aus angepasst werden.

Nehmen Sie dazu an, dass der beschriebene Tagesverlauf Ihrem Alltag entspricht und machten Sie sich mit der App vertraut. Wählen Sie dann Ihre gewünschten Standardeinstellungen aus. Diese Standardladeeinstellung beruht auf zwei Werten:

- **"Mindestreichweite sofort":** Die Reichweite, auf die Ihr Elektroauto direkt ohne Unterbrechungen geladen wird. Ihr Elektroauto wird dabei mit der maximal möglichen Ladeleistung von 70 km Reichweite pro Stunde aufgeladen.
- **"Mindestreichweite später":** Die Reichweite, die Ihr Elektroauto mindestens bis zum nächsten Gebrauch haben soll. Ihr Elektroauto wird dabei in einem flexiblen Modus geladen, d.h. der Ladevorgang kann kurzzeitig unterbrochen werden.

Sie fahren mit Ihrem Elektroauto ins nahegelegene Einkaufszentrum (10 km). Ihr Fahrzeug ist zu 50% geladen, was einer Reichweite von 175 km entspricht. Während Ihres drei-stündigen Aufenthalts können Sie auf dem Parkplatz des Einkaufzentrums laden.

Bitte stellen Sie Ihre Ladeeinstellungen ein.

Figure D.7.: Question group *Shopping center charging scenario (control group)* I.

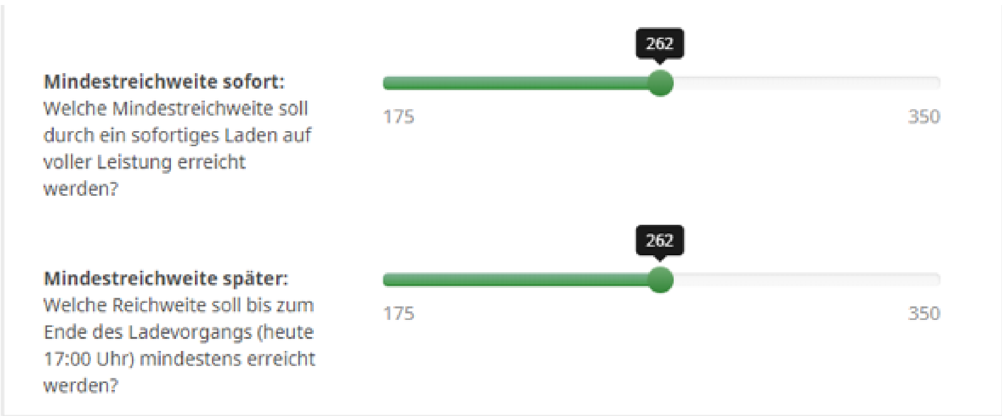
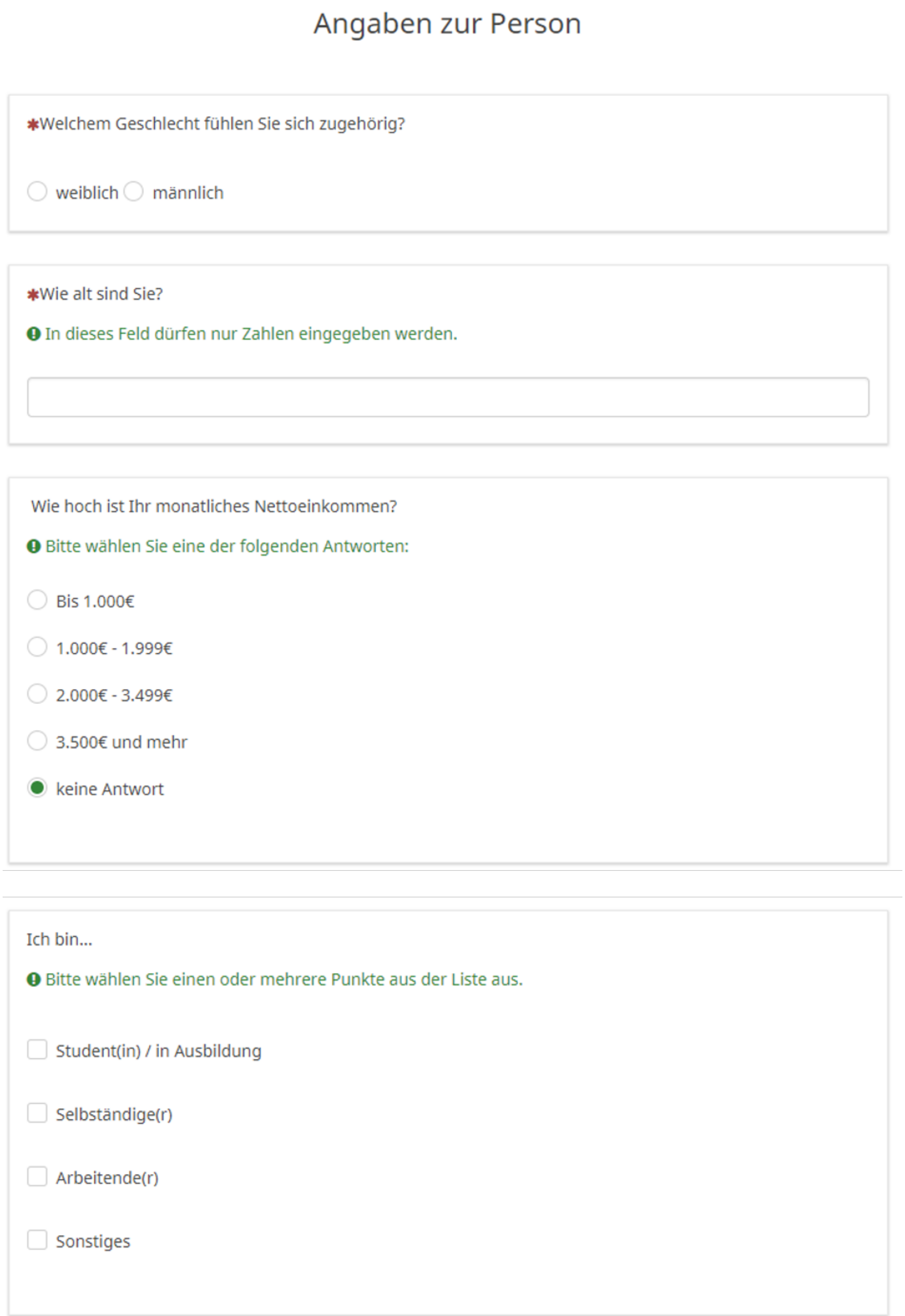


Figure D.8.: Question group *Shopping center charging scenario (control group)* II.



Angaben zur Person

*Welchem Geschlecht fühlen Sie sich zugehörig?

weiblich männlich

*Wie alt sind Sie?

In dieses Feld dürfen nur Zahlen eingegeben werden.

Wie hoch ist Ihr monatliches Nettoeinkommen?

Bitte wählen Sie eine der folgenden Antworten:

Bis 1.000€

1.000€ - 1.999€

2.000€ - 3.499€

3.500€ und mehr

keine Antwort

Ich bin...

Bitte wählen Sie einen oder mehrere Punkte aus der Liste aus.

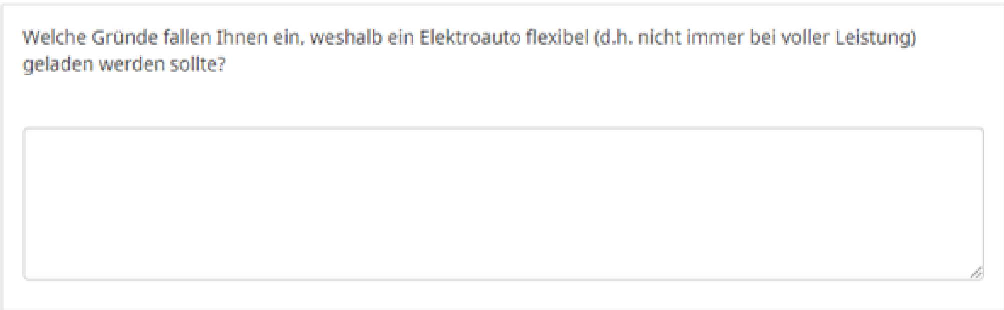
Student(in) / in Ausbildung

Selbständige(r)

Arbeitende(r)

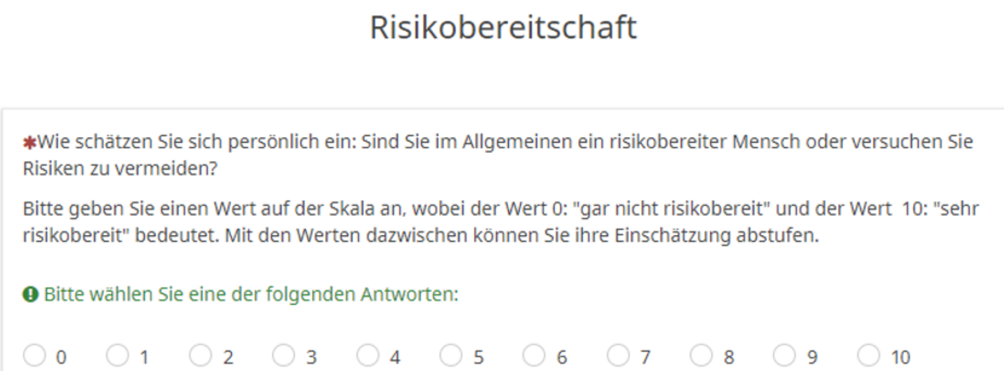
Sonstiges

Figure D.9.: Question group *Sociodemographic attributes*.



Welche Gründe fallen Ihnen ein, weshalb ein Elektroauto flexibel (d.h. nicht immer bei voller Leistung) geladen werden sollte?

Figure D.10.: Question group *Knowledge about flexible charging.*



Risikobereitschaft

*Wie schätzen Sie sich persönlich ein: Sind Sie im Allgemeinen ein risikobereiter Mensch oder versuchen Sie Risiken zu vermeiden?

Bitte geben Sie einen Wert auf der Skala an, wobei der Wert 0: "gar nicht risikobereit" und der Wert 10: "sehr risikobereit" bedeutet. Mit den Werten dazwischen können Sie ihre Einschätzung abstufen.

Bitte wählen Sie eine der folgenden Antworten:

0 1 2 3 4 5 6 7 8 9 10

Figure D.11.: Question group *Willingness to take risks.*

*Bitte geben Sie ehrlich an, wie die folgenden 10 Aussagen auf Sie zutreffen.

	trifft überhaupt nicht zu	trifft eher nicht zu	weder noch	trifft eher zu	trifft voll und ganz zu
Ich bin eher zurückhaltend, reserviert.					
Ich schenke anderen leicht Vertrauen, glaube an das Gute im Menschen.					
Ich bin bequem, neige zur Faulheit.					
Ich bin entspannt, lasse mich durch Stress nicht aus der Ruhe bringen.					
Ich habe nur wenig künstlerisches Interesse.					
Ich gehe aus mir heraus, bin gesellig.					
Ich neige dazu, andere zu kritisieren.					
Ich erledige Aufgaben gründlich.					
Ich werde leicht nervös und unsicher.					
Ich habe eine aktive Vorstellungskraft, bin fantasievoll.					

Figure D.12.: Question group *Personality and agreeableness.*

Fahrverhalten

*Besitzen Sie einen gültigen Führerschein?

○ Ja ○ Nein

*Im Durchschnitt, wie oft fahren Sie ein Auto?

Bitte wählen Sie eine der folgenden Antworten:

○ Täglich
○ Mehrmals in der Woche
○ Einmal pro Woche
○ Mehrmals im Monat
○ Einmal im Monat
○ Seltener
○ Nie

*Besitzen Sie ein eigenes Auto?

○ Ja ○ Nein

*Besitzen Sie ein E-Bike?

○ Ja ○ Nein

Bitte schätzen Sie, welche Strecke Sie (in km insgesamt) wochentags unabhängig vom Verkehrsmittel zurücklegen.

In dieses Feld dürfen nur Zahlen eingegeben werden.

Figure D.13.: Question group *Car related attributes*.

Umweltbewusstsein

*Geben Sie bitte an, wie sehr Sie den Aussagen zustimmen oder nicht zustimmen.

	Stimme voll und ganz zu	stimme weitgehend zu	weder noch	stimme eher nicht zu	stimme überhaupt nicht zu
Es beunruhigt mich, wenn ich daran denke, unter welchen Umweltverhältnissen unsere Kinder und Enkelkinder wahrscheinlich leben müssen.	○	○	○	○	○
Wenn wir so weitermachen wie bisher, steuern wir auf eine Umweltkatastrophe zu.	○	○	○	○	○
Wenn ich Zeitungsberichte über Umweltprobleme lese oder entsprechende Fernsehsendungen sehe, bin ich oft empört und wütend.	○	○	○	○	○
Nach meiner Einschätzung wird das Umweltproblem in seiner Bedeutung von vielen Umweltschützern stark übertrieben.	○	○	○	○	○
Es ist noch immer so, dass die Politiker viel zu wenig für den Umweltschutz tun.	○	○	○	○	○
Zugunsten der Umwelt sollten wir alle bereit sein, unseren derzeitigen Lebensstandard einzuschränken.	○	○	○	○	○
Es gibt Grenzen des Wachstums, die unsere industrialisierte Welt schon überschritten hat oder sehr bald erreichen wird.	○	○	○	○	○
Derzeit ist es immernoch so, dass sich der größte Teil der Bevölkerung wenig umweltbewusst verhält.	○	○	○	○	○
Umweltschutzmaßnahmen sollten auch dann durchgesetzt werden, wenn dadurtch Arbeitsplätze verloren gehen.	○	○	○	○	○

Figure D.14.: Question group *Environmental consciousness.*

APPENDIX E

REGRESSION MODEL FOR THE INFLUENCE OF FRAMING ON CHARGING FLEXIBILITY WITH ALL CONTROL VARIABLES

Table E.1.: Full regression model for the influence of framing on charging flexibility with all control variables.

Variable	Coefficient	Std. Error	t-Statistic	P>|t|
Intercept	0.5096	0.124	4.123	0.000
Framing[Cost]	0.0919	0.041	2.246	0.026
Framing[Environmental]	0.0078	0.037	0.210	0.834
Framing[Social]	-0.1072	0.042	-2.525	0.013
Income [Low]	-0.0408	0.056	-0.734	0.464
Income [Medium]	-0.0958	0.054	-1.758	0.081
Income [High]	-0.0374	0.048	-0.781	0.436
Income [Very high]	-0.1279	0.048	-2.688	0.008
Age	-0.0007	0.001	-0.479	0.633
Bev Ownership	0.0276	0.038	0.724	0.470
Gender	-0.0225	0.039	-0.584	0.560
Willingnes to take Risk	0.0144	0.007	2.017	0.045
Environmentalism	0.0243	0.023	1.064	0.289

Dep. Variable:	Charging Flexibility	**R-squared:**	0.170
Model:	OLS	**Adj. R-squared:**	0.105
Method:	Least Squares	**F-statistic:**	2.586
No. Observations:	164	**AIC:**	-84.35

APPENDIX F

RELATED WORK ON FORECASING REGARDING BEVS

Table F.1.: Related work on forecasting regarding BEVs.

	Predicted Variable	Entity	Input Features	Data	Models
Arias and Bae (2016)	Charging load	BEV fleet	Weather, Historical load	Conventional trip data	Decision Trees
Xydas et al. (2013)	Charging load	BEV fleet	Calendar variables, Historical load	Conventional trip data	Support Vector Machines
Amini et al. (2015)	Charging load	Parking lot	Historical load	Power system load data, Assumptions on BEVs	ARIMA
Bikcora et al. (2016)	Charging load, Occupation	Charging station	Historical load of close charging stations	Charging station data	Generalized linear models
Ai et al. (2018)	Charging time	Household	Historical load	20 days of charging data from one household	Random Forrest, Naive Bayes, AdaBoost, GBoost, ANN

Table F.2.: Related work on simulation regarding BEVs.

	Predicted Variable	Entity	Input Features	Data	Models
Xing et al. (2019)	Charging load (spatial)	BEV fleet	Trip trajectories, departure time, assumptions	Conventional trip data	Explicit model
Kisacikoglu et al. (2018)	Charging load	Charging station	Historical load	20 BEVs charging loads	Fitted distributions
Zhang et al. (2014)	Charging load (spatial)	BEV fleet	Land Use, BEV population, parking behaviour	Conventional trip data	Monte-Carlo Simulation
Wang et al. (2019)	Charging load (location type)	BEV fleet	SoC, first travel, driving time, driving distance	Conventional trip data	Monte-Carlo Simulation
Yi and Bauer (2015)	Charging load (spatial)	BEV	Parking duration, SoC, time of arrival and departure	Conventional trip data	Explicit model
Omran and Filizadeh (2013)	Charging load (spatial), parking events	BEV fleet	Drivers decisions, SoC, parking duration, driving distance	Conventional trip data, assumptions on drivers' decisions	Location-specific fuzzy decision making system

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EIDESSTATTLICHE ERKLÄRUNG

Ich versichere wahrheitsgemäß die Dissertation bis auf die in der Abhandlung angegebene Hilfe selbständig angefertigt, alle benutzten Hilfsmittel vollständig und genau angegeben und genau kenntlich gemacht zu haben, was aus Arbeiten anderer und aus eigenen Veröffentlichungen unverändert oder mit Abänderungen entnommen wurde.

Karlsruhe, 25. Mai 2020

(Julian Christoph Huber)